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STUDY OF SEASONALITY, IMPACT OF PROMOTIONS AND DEMAND FORECASTING METHODS

Based on the example of a company

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ABSTRACT

Demand forecasting might be a challenging activity for any company. Actually, it is extremely difficult to predict the future trends, due to constant changes and increasing of complexity. An effective sales forecasting can become a core competence and help to surpass the competition. The present document was developed to assess the current ABC company's demand forecasting method and to understand which factors can influence the sales of the company. Therefore, an analysis of seasonality, impact of promotions and forecasting methods was conducted. Thus, in this report both a forecasting method for the subcategory Ice Cream and an adjustment of promotions were suggested, allowing then for more accurate forecasting results.

KEYWORDS

Demand, Demand Forecasting, Seasonality, Effect of Promotions, Forecasting Methods

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1- ACKNOWLEDGEMENTS

When one finishes his/her thesis, it seems that it is the end. I think that it is the beginning of a new adventure. An adventure where hard work, openness to new opportunities and persistence will be necessary.

Nonetheless, for me, this journey would never be about to start if wise and supportive special people had not crossed my path.

Hence, I feel pleased to have the chance to dedicate my work and express my gratitude to the incredible and unique people that I had the pleasure to deal with during my thesis.

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I would like to thank to F., Director of Supply Chain of the ABC company, for his appropriate advice and availability, it was a pleasure to meet him. I have to give special thanks to J., N. and N. for their guidance and for providing essential information.[1]

I could not also finish without expressing my sincere gratitude for extraordinary and motivational professors that I had the chance to learn from in my Master's degree. The knowledge that they shared with me was fundamental to my progress and for sure they became inspirational people to me.

Last but not least, I have to thank my family and friends. They have been so wonderful, supportive and I am so lucky to have them in my life, I could never feel the same drive to achieve my objectives if they did not motive me every day and transmit me their love.

[1] Please, consider that these names were deleted due to a confidentiality agreement.

2- INTRODUCTION

The present document was developed during the ABC company's Thesis Programme[2], a programme where students can develop their thesis project with the company concerned. This work had the supervision of Professor Manuel Pedro Baganha, professor of Nova School of Business and Economics in the areas of Supply Chain and Operations, as well as ABC company's Supply Chain Director.

The ABC company is a Portuguese retail company, which has a large number of stores spread all over the country, with different dimensions – hyper (over than 2,000 square meters), mega (between 600 and 2,000 square meters) and super (under 600 square meters). This study will focus on a store with characteristics of a hyper, in Lisbon.

The ABC company's products are classified as follows (Figure 1):

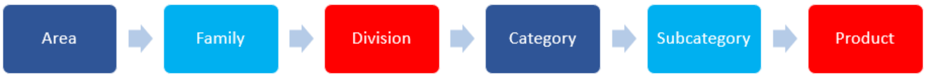


Figure 1: ABC company's framework for categorisation of products

The company has many levels of specification of a product. The most extensive level of specification is the area and the most precise level is the product itself. The areas of ABC company are the following: Grocery Products, Specialised Perishables Products, Not Specialised Perishable Products, Beverages, Detergents and Cleaning Products, Personal Products, Bazaar Products, Electronic and Entertainment Products, Textile and ABC Company's Textile.

This specific study will examine the impact of seasonality and promotions. Moreover, it will analyse forecasting methods, including the current forecasting method of the company.

The objective of this study is to improve performance of the present demand forecasting system in order to avoid stock outs or excess of stock. The ultimate goal is to help the company optimise

[2] Attributable to confidentiality reasons the company's name was renamed to ABC company.

sales in order to be more efficient and reduce costs. Hence, the main research question is: How can the company improve its current forecasting system?

3- RELATED LITERATURE

3.1- CONTEXTUALIZATION

The Portuguese retail industry is showing a considerable growth since consumers are expressing more confidence and optimism. Several companies are investing in new stores to get closer to their consumers, following a proximity concept (Euromonitor International, 2018). However, retail companies need to face a strong competition and other challenges, such as globalisation, technological progress, innovations and demand uncertainties. Customers are demanding more and suppliers are responding by providing a better service and better customer experience (Foster, 2013). So as to be competitive and relevant, retail companies need to understand the behaviours and dynamics of the purchasing, as well as have a deep knowledge of their target consumers (GfK Portugal, 2018).

An effective demand forecasting system is essential to be developed. Thus, the demand projections are important for companies not only in a strategic level but also in a tactic level (Carvalho *et al*., 2017). Obtaining data and knowledge of the factors and risks that might influence the demand is vital; without them it is not possible to achieve real and precise objectives (Caiado, 2016). They allow the company to react to demand changes quickly and with more flexibility, to increase availability of products in the market and to develop competitive advantage (Vlčková, 2009).

3.2- IMPORTANCE OF FORECASTING

Forecasting becomes a crucial part of any company (Waters, 1992). There are several forecasting methods, but none of them can be considered ideal in all occasions. It is necessary to understand the seasonality, complexity and perishability of the products to choose the best method for each situation (Veiga *et al*., 2014). In reality, Waters (1992) stated that simple methods could give good results and are more economical than complex ones.

Furthermore, a poor forecast does not only bring financial losses and inefficiency but also modifications in the consumers' shopping behaviour. Actually, Fitzsimons (2000) claimed that it is less likely for consumers to return to the same store on their following shopping trip if they are previously subjected to a stock-out.

The forecasting problems that companies are currently facing consist on their difficulty to comprehend company's data bias, lack of understanding of the value of their data, the difficulty to examine their massive quantity of data and incapacity to combine internal and external data (Nanda *et al*., 2018).

The world is moving at a faster pace. Also, markets, consumer segments and channels are increasingly more complex (Nanda *et al*., 2018). Companies are dealing with many challenges. The existence of mature markets is one of them, which makes companies resort to more innovations and promotions to maintain sales and encourage growth. Another challenge is the constant evolution of consumer behaviour. Customers have higher expectations, and therefore companies need to constantly reassess their products and their fulfilment strategies. Finally, costs are rising mostly due to the stronger competition from new channels and new players (Caillet *et al.*, 2017). Hence, it is imperative for companies to adopt demand planning and forecasting strategies. The benefits are enormous, from reducing inventory and operational costs, having a better customer service, cultivating supplier relationships, decreasing stock, reducing lost sales and obsolescence, and improving forecast accuracy and on-shelf availability (Nanda *et al*., 2018).

According to Caillet *et al.* (2017), companies should benefit from advanced statistical models and specific information, such as past sales and promotional data, weather forecasts, pricing fluctuations, inventory levels, prices of the competitors and social media trends. Moreover, companies should rely on “demand planning”, preparing what-if analyses using drivers such as demand, marketing and sales information. Nowadays companies should also rely on “demand sensing”, understanding demand signals and forecasting in real time. In a technological era, companies should take advantage of the technologies, for instance big data, advanced statistical modelling, digital technologies and predictive analytics.

Several companies use ERP (Enterprise Resource Planning) software to calculate their forecasts. Nonetheless, most of the time, this software does not adapt to the constant changes of the markets and to the new trends, since it is rigid in its methodology and it may not recognize the negative impact of some retailer behaviours, as order policies and promotions (Myerholtz *et al.*, 2014).

3.3- IMPACT OF SEASONALITY IN THE DEMAND

In addition, seasonality is a reality that can make any company struggle if they do not understand how to tackle it. Pearson (2015) specified four causes for seasonality. One of them is “calendar effects”, which are events that happen in the same calendar month with comparable dimension from year to year, for example Valentine’s Day and Christmas. Furthermore, moving holidays (Easter, for instance) and trading-day effects (variations of weekends and weekdays year to year) can bring more complexity to forecasting. Another cause is “timing decisions”, which are dates for events that do not depend on the calendar, an example of which is the selection of a company fiscal year. Another cause is the “weather”, as the natural precipitation and temperature in an area can reduce or increase the consumption of certain products or services. Finally, the last cause mentioned is “expectations”, for they actually generate seasonality. For instance, mid-Autumn Christmas advertising raises expectations, by modifying the typical time that people do Christmas shopping.

Seasonal products were categorised by Småros (2012) according to some variables, such as lead time of purchases, length of the season and life cycle of the product. This author also describes that it is better to link the index of seasonality to the event itself, for instance Easter, and not to a given week or day. Additionally, the author defends that a forecast which relies on historical data and that considers seasonal variations is sufficient to guarantee the replenishment of perennial products during the year.

Generally, aggregate forecasts are more accurate than disaggregate forecasts (i.e. individual products) since compensation effects in random components can affect individualised sales. Hence, it is easier to identify tendencies or seasonality in aggregate forecasts. The aggregation can be done according to categories or families of products, temporal (for instance day or month), spatial (for example area) or types of customers (Carvalho *et al*., 2017).

3.4- IMPACT OF PROMOTIONS

Sales cannibalisation can be a consequence of promotions. A promotion reduces the sales of a specific product caused by the commercialisation of another similar product in promotion, in the same company. The cannibalisation is higher when the degree of substitution between the promoted product and others without promotion is greater. In fact, a promotion in a SKU (stock keeping unit) or group of SKUs frequently cannibalises similar products within the company (Oracle, 2006).

Retailers have a hard time to manage their promotions. Generally, promotions are only evaluated according to the increase of sales of those promoted products. However, it is important to notice the adverse effects of promotions such as cannibalisation (Bacos *et al.*, 2017). The cannibalisation is very frequently underestimated, consequently it originates a dramatic overestimation of the promotional benefits (Isotta *et al*., 2013). In fact, the cannibalisation becomes difficult to measure since it can influence a huge number of products (Oracle, 2006).

3.5- METHODS OF DEMAND FORECASTING

There are many forecasting methods that the companies can rely on, from qualitative methods (subjective and expectative) to quantitative methods (from historical data) (Carvalho *et al*, 2017).

The present study will focus on quantitative methods, such as simple moving average, simple exponential smoothing and ARIMA models.

The moving average method is used to estimate the current level of a time series (Johnston *et al*., 1999) and can be considered reasonable to good in the short or medium term (Silva, 2016). Actually, it gives good results when the demand is constant or stable, and so it is appropriate for stationary time series data where the series has a constant variance throughout time.

Exponential smoothing method is a good method for demand stable over time. This method gives higher weight to most recent data than to older data, in fact, the weight reduces exponentially with less recent data (Silva, 2016).

Box and Jenkins in 1970 proposed an approach which includes the following steps: data preparation by transforming and differentiating the data, model selection in order to understand which possible ARIMA processes could fit the data, parameter estimations with the aim to find values of parameters which fit the data, model checking and forecasting (Hyndman, 2001). The ARIMA approach includes the principle of parsimony, which provides the simplest models that can suit the data, and the forecasts are based on linear functions of the sample observations (Hyndman, 2001). ARIMA(p,d,q) stands for autoregressive (AR), integrated (I) and moving average (MA), considering that AR(p) defines how each observation is a function of the previous "p" observations while MA(q) defines how each observation is a function of the previous q errors (Hyndman, 2001). AR(p) (Autoregressive model of order p) can be expressed as:

$$X_t = \sum_{r=1}^{p} \phi_r X_{t-r} + e_t \tag{1}$$

Considering that ϕ_1 ... ϕ_r are fixed constants, $\{e_t\}$ is a sequence of independent random variables (mean 0 and varianceσ^2) (University of Cambridge, 2018).

Moreover, MA(q) can be expressed as:

$$X_t = \sum_{s=0}^{q} \theta_s e_{t-s} \tag{2}$$

Also, note that $\theta_1, \ldots \theta_q$ represent fixed constants, θ_0=1, also $\{e_t\}$ represents a sequence of uncorrelated random variables (mean 0 and variance σ^2) (University of Cambridge, 2018). There are some metrics to check the accuracy of demand forecasting methods, and their aim is to calculate the extent to which the model fits the data. The most common ones are Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Their computations are subsequent expressed:

$$MAE = \frac{1}{m} \sum_{t=1}^{m} |Y_t - P_t| \tag{3}$$

$$MSE = \frac{1}{m} \sum_{t=1}^{m} (Y_t - P_t)^2 \tag{4}$$

$$RMSE = \sqrt{\frac{1}{m} \sum_{t=1}^{m} (Y_t - P_t)^2} \tag{5}$$

$$MAPE = \frac{1}{m} \sum_{t=1}^{m} \left| \frac{(Y_t - P_t)}{Y_t} \right| 100 \tag{6}$$

where $Y_t$is the actual value and P_t the forecast value.

MAE does not include the direction of the forecasts**.** RMSE conserves the units of the estimation variable. With MAPE it is possible to compare distinct time-series data without defining the relation or percent error (Permatasaria, 2018).

Bearing the related literature in mind, companies need to pay attention to their forecasts and create mechanisms that integrate knowledge, expertise and technology in order to address constant challenges. Improving forecasting method allows for fewer missed sales, higher customer-service levels, lower working capital, more efficient manufacturing, less waste and reduced efforts (Myerholtz *et al.*, 2014).

4- ACTUAL ABC COMPANY'S DEMAND FORECASTING SYSTEM

ABC company's department of Supply Chain has the responsibility of managing the orders of the stores and their replenishment. The company uses the SAP (System Applications Products), an ERP (Enterprise Resource Planning) software, to integrate all departments, facilitating the information flow. The company also uses the MRP (Materials Requirements Planning), in which the necessary quantities to send to each store are calculated, taking into account the lead times of the suppliers and the inventory levels. The calculation is automatic and processed on Sunday overnight. The platform specifies the quantity of each product, for each day of the following week. However, every day, during the night, after the stores are closed, the MRP is updated to the current reality. The manager of each store has the possibility to change the quantities suggested by the MRP. Nevertheless, in most cases changing these quantities usually leads to stock-outs or excess of stock.

It is also noteworthy to mention that the company is under a pull system, since the demand of the store pulls the distribution, which means that after the orders of the stores are processed, the supply chain is triggered.

The ABC company's demand forecasting method is described as consisting on the average of the sales of the last four weeks of the current year compared with the corresponding last four weeks of the previous year, through the calculation of a seasonal index. Thus, the company considers the demand seasonality on their forecasting method. [3]

Provided a product is in promotion in any of those four weeks, that week is not incorporated in the calculation, i.e. the company is using merely the sales without promotions as the baseline for its forecasts. The MRP also considers the actual stock, taking into consideration two components: theoretical coverage (the store has to ensure a specific stock level during a particular length of time, for example, if a supplier only delivers the product every three days, the theoretical coverage is three) and safety stock (the minimum stock for each product in any store was defined to be four units, this number was chosen in order to fulfil the shelf to give a better image for the customer). In the end, the highest number between both components is chosen. In fact, the products that have higher turnover are usually based on the theoretical coverage while the products that have a lower turnover are frequently based on the safety stock.

5- THE PROBLEM

The company noticed that its MRP is not satisfactory reactive when changes of demand occur which were not automatically predicted, i.e. the parameters are extremely fixed. For instance, imagine that last year in the four last weeks there was a heat wave, leading to an increase in the sales of the product "ice". This will result in the MRP estimating the stock for the corresponding four weeks in the following year on the basis of that increase in sales, which means that the MRP will order more ice than the necessary for that period. Thus, the company was wrongly influenced by a specific cause that the MRP was not able to predict or react to. Hence, the company should recognise the importance of monitoring the performance of its current demand

[3] Since the company did not provide real past forecasting data, this definition of the current forecasting method is an estimation based on what was told in the meetings with the company.

forecasting methods. It is also vital to set strategies to improve its forecasting processes and reduce its stock outs and excess of inventory.

In addition, a study on the causes of stock outs in a specific store was conducted, but due to the lack of information in due time regarding the hyper store, the study of stock outs was exceptionally based on a super in Lisbon, during the months of October and November of 2017 (see Appendix 1). There are many causes of stock outs, such as forecasting errors, service level, delays, risk coverage, reactive and/or new product, modifications of the MRP, peak of sales and problems with master data. The service level (22.37%) and promotions (21.03%) were the causes that had higher weight. Besides, the forecasting errors represented 5.17% of the total causes whereas the peak of sales represented 1.18%. Regarding the cause of forecasting errors, it was observed that Not Specialised Perishable Products (37.46%) and Specialised Perishable Products (20.97%) were the areas in which had more stock outs. Concerning the cause of promotion, it was noticed that the areas of Personal Products (29.79%) and Detergents and Cleaning products (22.05%) were the more affected ones with stock outs. Finally, it could be verified that there were more stock outs caused by peak of sales in the areas of Not Specialised Perishable Products (42.19%) and Specialised Perishable Products (40.63%).

6- METHODOLOGY

A study of seasonality, impact of promotions and demand forecasting models was presented of store located in Lisbon with the characteristics of a hyper. The key research questions of this thesis are: What are the main problems with the company's forecasting system? To what extent does seasonality influence the demand? What is the impact of promotions on the company's demand? Is the current forecasting method of the company sufficiently accurate compared to other forecasting methods?

This document used quantitative techniques. Regarding seasonality, the sales and number of transactions of five products were analysed. Concerning the study of the impact of promotions, an analysis of the sales of two products of the company's white brand was conducted. In what concerns demand forecasting models, the programs EViews and EXCEL were used to estimate these methods.

7- CONDUCTED ANALYSIS OF THE WORK PROJECT

7.1- STUDY OF SEASONALITY

According to the company, the concept of seasonality is defined by any variation that can happen in the last four weeks of the current year when compared to the same period in the last year. The company computes the seasonality every week, calculating seasonal factors.

To prove that ABC company is under the effect of seasonality, five areas of products of the hyper in question were analysed. The chosen ones were: Not Specialised Perishable Products, Grocery Products, Personal Products and Beverages. In each area a particular product was studied. The elected products were ice cream, infusions, deodorant, laundry detergent pod, and ice tea. The selection of these products was obtained taking into account their relevance for the hyper store. The company provided daily data of the sales of these products during 2016 and 2017; however, it was subsequently aggregated into weeks due to the current forecasting procedure of the company.

The existence of seasonality can be confirmed through the figures presented in Appendix 2. There was a similarity in the pattern of total sales (with and without promotions) between the years considered, 2016 and 2017, in all the products analysed, considering that the ice tea product had an abnormal behaviour in 2016 due to a significant promotion.

Also, the same analysis was conducted using sales without promotions in order to understand if the results would differ (see Appendix 3). It was concluded that there is less similarity between both years when the promotions were not included, mainly due to the fact that the sales of promoted products are not being counted, however they account for a significant portion of the company's total sales.

A deeper investigation of seasonality for the five previous analysed products was carried out (see Appendix 4), through the evaluation of the sales and the number of transactions (number of tickets) during the years of 2016 and 2017, with the separation of the promoted products and products without promotions. Additionally, the same analysis for ABC company's products of own-label brand (ice tea and ice cream) was made.

The conclusions were the following:

- The ice cream obtained a higher consumption in the Spring and Summer. The promotions influenced the purchase of this product.
- The white brand of ice cream of ABC company was not much influenced by the promotions.
- A higher consumption on infusions was observed in the Winter and Autumn months. The promotions did not have much impact on the purchase of this product.
- The purchase of deodorants was extremely influenced by the promotions. It was observed that in any month of the year, the last week of the month obtained higher sales than the other weeks. Also, in 2016, there was an increase in sales during the first months of the year whereas in 2017 this was not observed.
- Concerning the laundry detergent pod, the promotions impacted greatly on the sales of this product. Customers tend to buy this product during the first and last week of the month.
- Sales of ice tea showed a higher value during the Summer months and special celebrations as Christmas. Otherwise, its consumption was regular.

- The impact of promotions of the ice tea was lower on the white brand product than on the other brands.

7.2- STUDY OF THE IMPACT OF PROMOTIONS

Indeed, promotions can impact seriously on the demand forecasting, creating complexity. Most of the time, an incorrect demand forecasting creates surplus stock or generates spoilage. It is true that when a certain product is on promotion, it can generate secondary effects in other products which were not in promotion at that time. Cannibalisation and halo relationships are concepts that become important to refer and are not being accounted in the MRP of the company. Note that halo relationships are related to the connection of supplement products, for instance a specific product might increase its sales if its complementary product is on promotion (Viitanen, 2018). Actually, these effects are extremely difficult to measure and to model, they can become diffuse and influence an extensive range of products that are unrelated.

To prove that ABC company was under the influence of these effects, an analysis of the cannibalisation effect of two products of white brand (ice tea and ice cream) was made (see Appendix 5). The analysis was based on the daily data of 2017 provided by the company. The daily data was aggregated in weeks.

It is expected that when there is a promotion of the white brand product, the sales of that product increase. This was confirmed in all quarters of 2017 for both products analysed. Although it has been concluded that when the promotion occurred in two weeks in a row, the cannibalisation effect was more visible in the first week of the promotion, as shown in Figure 2.

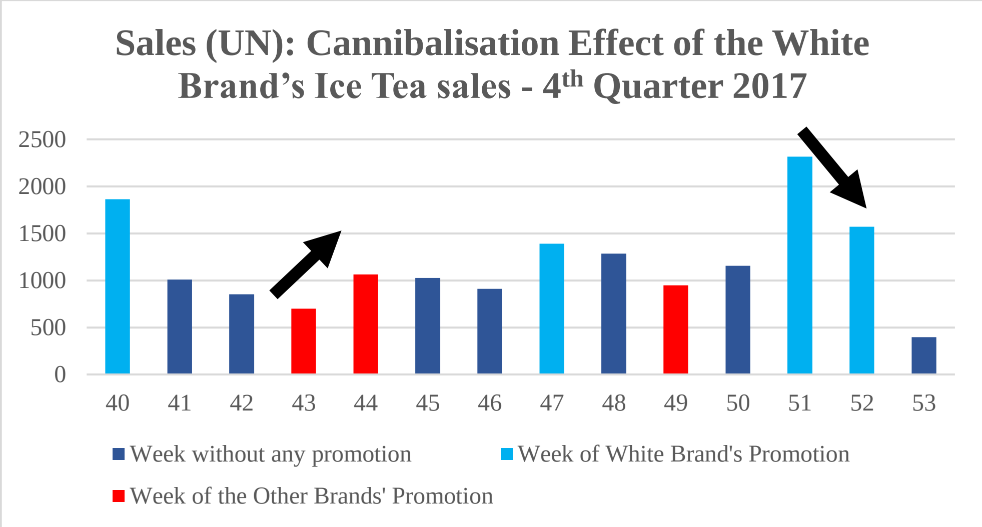


Figure 2: Sales (UN): Cannibalisation Effect of the White Brand's Ice Tea sales - 4th Quarter 2017

If other brands of similar products were on promotion, it was possible to verify that there was a decrease in sales of the white brand in these weeks, confirming the influence of a cannibalisation effect. Also, in case the promotion occurred two weeks in a row, the influence of cannibalisation was higher on the first week of the promotion. This can be proved in the first quarter of 2017 of the ice tea product (Figure 2).

ABC company's sales are extremely influenced by promotions. Therefore, a study of the impact of promotions was carried out using the data of the products that this work is focusing on: ice cream, infusions, deodorant, laundry detergent pod and ice tea (see Appendix 6).

A formula was developed:

$$Y_t = \frac{Y_{t-1}+Y_{t-2}+Y_{t-3}+Y_{t-4}}{4} + effect\ of\ the\ promotion \tag{7}$$

where Y_t corresponds to the Total Sales and $\frac{Y_{t-1}+Y_{t-2}+Y_{t-3}+Y_{t-4}}{4}$ to the average of the sales of the last four weeks without promotions.

This formula was created in order to understand the capability of the current demand forecasting method (average of the last four weeks without promotions) to explain the total sales and to recognise the impact of the promotions in the total sales. The conclusions were that the deodorant and laundry detergent pod were the products more influenced by promotions, i.e. they presented a higher "effect of the promotion" portion in the total sales, whereas the products that were less influenced were infusions and white brand of ice cream and ice tea.

The main conclusion of this study was that the principal demand forecasting method of the company is not enough to forecast the total sales since they are enormously influenced by the promotions that the company does. Therefore, the company should develop a forecasting method that also includes the impact of promotions. Currently, the company forecasts the sales of promoted products according to similar past promotions that occurred in the last years, for instance in accordance with the discount of promotion (e.g. 25% or 50% of discount) and time of year. However, due to the high impact of the promotions in the sales of this company, there is the need to devise a new, more accurate mechanism, which monitors the impact of promotions.

7.3- ANALYSIS OF BOX-JENKINS APPROACH

7.3.1- DATA

The company provided data on daily "Take Home Ice Cream" subcategory sales. This specific subcategory was chosen since it is a representative subcategory in the hyper and it is a product with seasonal behaviour. The daily sales of products that were on promotion, with special commercial campaigns, were excluded from the analysis since the company only uses baseline sales without promotions in its forecasting. Furthermore, the data was aggregated in weeks, following the company's forecasting methodology. The final series used had 106 observations, including the weeks from 27th December 2015 to 31st December 2017 (Figure 3).

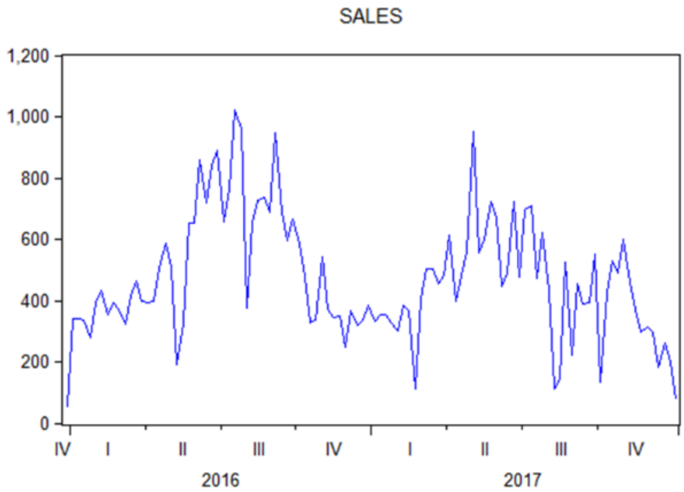


Figure 3: Sales of Take Home Ice Cream Without Promotions –2016 and 2017 - Units

The series appears to have quarter seasonality. In fact, higher sales are associated with Spring and Summer months. To check this behaviour, some descriptive statistics were computed using quarters as categories (Table 1).

Table 1: Descriptive Statistics of Sales of Take Home Ice Cream Without Promotions in the studied period.

QUARTER	Mean	Median	Max	Min.	Std. Dev.	Obs.
1	361.0385	362.5000	503.0000	57.00000	101.1642	26
2	566.4615	559.5000	951.0000	190.0000	174.9535	26
3	593.3462	636.5000	1023.000	113.0000	238.2983	26
4	367.4643	347.5000	665.0000	75.00000	141.0171	28
All	470.1038	433.0000	1023.000	57.00000	200.4330	106

Note: Yellow values represent: higher mean, higher median, the maximum, the minimum, higher standard deviation

As may be seen, quarters 2 and 3 have higher median and higher maximums while quarters 1 and 4 appear to have less sales, presenting minimums near the overall minimum and means lower than the overall mean.

The sales plot also shows an autocorrelation behaviour and little mean reversion. This indicates that the series stationarity should be investigated. Thus, a correlogram was computed (Figure 4).

Sample: 12/27/2015 12/31/2017
Included observations: 106

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.606	0.606	40.032	0.000
		2	0.474	0.170	64.812	0.000
		3	0.509	0.272	93.575	0.000
		4	0.433	0.035	114.57	0.000
		5	0.335	-0.03...	127.29	0.000
		6	0.290	-0.02...	136.90	0.000
		7	0.313	0.095	148.21	0.000
		8	0.227	-0.06...	154.21	0.000
		9	0.171	-0.02...	157.66	0.000
		1...	0.077	-0.16...	158.37	0.000
		1...	0.078	0.034	159.11	0.000
		1...	0.050	-0.02...	159.42	0.000
		1...	-0.04...	-0.08...	159.71	0.000
		1...	-0.09...	-0.09...	160.89	0.000
		1...	-0.11...	-0.04...	162.62	0.000
		1...	-0.14...	-0.03...	165.32	0.000
		1...	-0.19...	-0.01...	170.17	0.000
		1...	-0.18...	-0.00...	174.80	0.000
		1...	-0.27...	-0.17...	184.85	0.000
		2...	-0.30...	-0.05...	197.24	0.000
		2...	-0.33...	-0.09...	212.32	0.000
		2...	-0.41...	-0.13...	235.42	0.000
		2...	-0.38...	-0.00...	255.66	0.000
		2...	-0.34...	0.027	271.96	0.000
		2...	-0.36...	-0.04...	290.62	0.000
		2...	-0.33...	0.057	306.58	0.000
		2...	-0.26...	0.040	316.97	0.000
		2...	-0.27...	-0.02...	328.26	0.000
		2...	-0.24...	0.031	337.09	0.000
		3...	-0.22...	-0.06...	345.01	0.000
		3...	-0.21...	-0.01...	351.75	0.000
		3...	-0.16...	0.006	355.93	0.000
		3...	-0.08...	0.104	357.00	0.000
		3...	-0.07...	-0.02...	357.83	0.000
		3...	-0.06...	-0.05...	358.56	0.000
		3...	0.020	0.032	358.63	0.000

Figure 4: Autocorrelation function and Partial Autocorrelation function of Sales of Take Home Ice Cream - 2016 and 2017

The correlogram for sales is characterised by a slow sinusoid decay in the autocorrelation function and a quick decrease to zero in the partial autocorrelation function. This indicates a potential nonstationary behaviour in sales series. To test the existence of a unit root, Augmented Dickey-Fullr test (ADF) was conducted using the following auxiliary regression (see Appendix 7):

$$\Delta sales_t = \theta y_{t-1} + \delta_0 + \delta_1 \Delta sales_{t-1} + \delta_1 \Delta sales_{t-2} + u_t \quad (8)$$

The intercept was included because sales had mean different from zero. Additionally, a deterministic trend could have been included, but the existence of a trend would imply that sales could increase indefinitely, what does not seem very reasonable.

The ADF test resulted in an observed test statistic of -2.26 to which corresponds an observed p-value of 0.1870 (Table 2). Thus, the null is not rejected using the usual significance levels (1%, 5% and 10%). So, there is statistical evidence of nonstationary behaviour in sales. Therefore, the series may not be used prior to differentiation.

Table 2: Augmented Dickey-Fuller Test for Sales of Ice Cream Without Promotions – 2016 and 2017

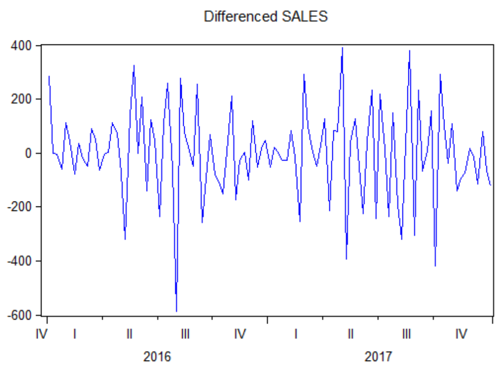
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.259872	0.1870
	1% level	-3.495021	
Test critical values:	5% level	-2.889753	
	10% level	-2.581890	

After this procedure, the ADF test was repeated to ensure the sales differences were stationary (Table 3). The ADF observed test statistic was -12.06 which is lower than the critical values for the usual significance levels. Thus, it is possible to reject the null hypothesis that the series has a unit root.

Table 3: Augmented Dickey-Fuller Test for the 1st Difference of Sales of Ice Cream Without Promotions – 2016 and 2017

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.06217	0.0000
Test critical values:	1% level	-3.495021	
	5% level	-2.889753	
	10% level	-2.581890	

Finally, a log transformation was made to mitigate possible heteroscedasticity behaviour: variance not being constant throughout the time (Figure 5). The use of log differences also brings interpretability advantages, once it represents the sales growth rate. Moreover, a seasonal differentiation should be considered. However, due to the short period of time (two years), a considerable number of observations would be lost, which could jeopardise the generalisation capacity of the model.



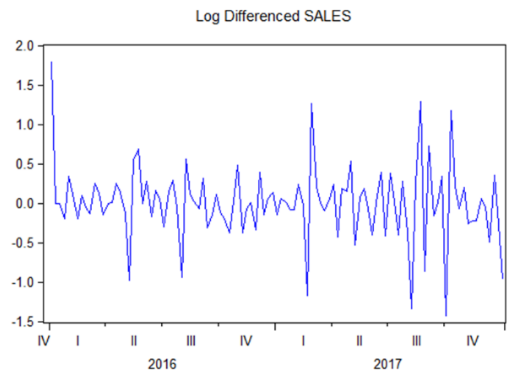
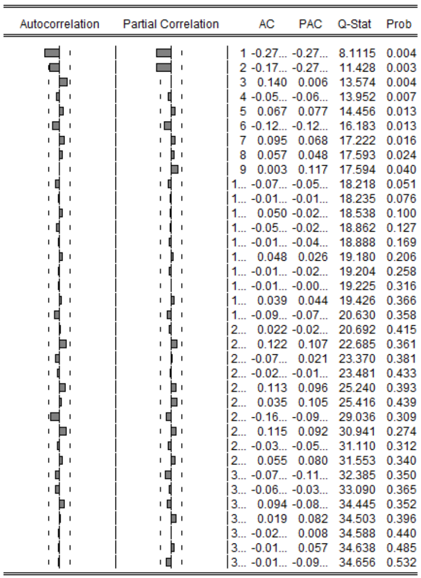


Figure 5: 1st Difference and Log Differenced Take Home Ice Cream Sales Without Promotions

7.3.2- MODEL ORDER IDENTIFICATION

Once stationarity has been addressed, the order identification follows (i.e. the p and q) of the autoregressive and moving average terms. To do so, the correlogram of the first differences of the logarithmic sales was analysed.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.27...	-0.27...	8.1115	0.004
		2	-0.17...	-0.27...	11.428	0.003
		3	0.140	0.006	13.574	0.004
		4	-0.05...	-0.06...	13.952	0.007
		5	0.067	0.077	14.456	0.013
		6	-0.12...	-0.12...	16.183	0.013
		7	0.095	0.068	17.222	0.016
		8	0.057	0.048	17.593	0.024
		9	0.003	0.117	17.594	0.040
		1...	-0.07...	-0.05...	18.218	0.051
		1...	-0.01...	-0.01...	18.235	0.076
		1...	0.050	-0.02...	18.538	0.100
		1...	-0.05...	-0.02...	18.862	0.127
		1...	-0.01...	-0.04...	18.888	0.169
		1...	0.048	0.026	19.180	0.206
		1...	-0.01...	-0.02...	19.204	0.258
		1...	-0.01...	-0.00...	19.225	0.316
		1...	0.039	0.044	19.426	0.366
		1...	-0.09...	-0.07...	20.630	0.358
		2...	0.022	-0.02...	20.692	0.415
		2...	0.122	0.107	22.685	0.361
		2...	-0.07...	0.021	23.370	0.381
		2...	-0.02...	-0.01...	23.481	0.433
		2...	0.113	0.096	25.240	0.393
		2...	0.035	0.105	25.416	0.439
		2...	-0.16...	-0.09...	29.036	0.309
		2...	0.115	0.092	30.941	0.274
		2...	-0.03...	-0.05...	31.110	0.312
		2...	0.055	0.080	31.553	0.340
		3...	-0.07...	-0.11...	32.385	0.350
		3...	-0.06...	-0.03...	33.090	0.365
		3...	0.094	-0.08...	34.445	0.352
		3...	0.019	0.082	34.503	0.396
		3...	-0.02...	0.008	34.588	0.440
		3...	-0.01...	0.057	34.638	0.485
		3...	-0.01...	-0.09...	34.656	0.532

Figure 6: Correlogram for 1st Difference of Sales of Take Home Ice Cream - 2016 and 2017

According to Figure 6, there are two significant deviances of autocorrelation: MA(1) and MA(2) and two significant deviances of partial autocorrelation: AR(1) and AR(2), which leads to the following candidate models (see Appendix 7):

1 ARIMA(2,1,2);

2 ARIMA(2,1,2), restricted MA(1)=0;

3 ARIMA(2,1,2), restricted MA(1)=0, augmented by quarterly trend.

Below is a brief explanation of Akaike information criterion (AIC) and Schwarz criterion or Bayesian Information Criteria (BIC):

$$AIC = 2k - 2\log(\hat{L}) \tag{9}$$

where $\hat{L}$ is the maximum value of the likelihood function for the model. $2k$ increases as the number of parameters increase in the model, penalizing models that are complicated. $2\log(\hat{L})$ decreases as the model gets better at explaining the data (University of Adelaide, 2018).

$$BIC = klog(n) - 2\log(\hat{L}) \tag{10}$$

where $klog(n)$ increases as the number of parameters increases in the model but also as the number of observations in the data increases, penalizing the models that are complicated, with a larger penalty when working with a large amount of data. The smaller AIC and BIC the better (University of Adelaide, 2018).

Using Akaike information criterion (AIC), the third model is selected (Table 4).

Table 4: Akaike info criterion and Schwarz criterion

Model	**AIC**	**BIC**
ARIMA(2,1,2)	0.985210	1.087529
ARIMA(2,1,2), restricted MA(1)=0	0.962933	1.090832
ARIMA(2,1,2), restricted MA(1)=0, augmented by quarterly trend	0.894447	1.099086

Note: Yellow values represent the best model for each criterion

AIC was chosen since BIC is less tolerance at higher numbers and penalizes more the free parameters (Difference Between.net, 2010). Also, including more parameters might be better than omitting significant parameters (Stock *et al.*, 2007).

7.3.3- ESTIMATION AND FORECAST

In this section the chosen model is estimated, and its forecast performance evaluated. To do so, the sample was split into two: in-sample period and out-of-sample period. The in-sample period has 92 observations and goes from 27th December 2015 to 24th of September 2017, while the out-of-sample has 14 observations from 1st of October 2017 to 31st December 2017. The data set of the in-sample period was used for parameter estimation, and the out-of-sample period used to evaluate forecasting performance.

The final equation of the chosen model is subsequently presented:

$$\Delta \log Y_t = -0.0998 + 0.0096 * week + 0.0096 * Q_1 week + 0.0088 * Q_2 week - 0.0001 * Q_3 week - 0.6222 Y_{t-1} - 0.0036 Y_{t-2} - 0.7516 (P_{t-2} - Y_{t-2}) \quad (11)$$

This model includes quarterly trends, captured by Q_1week, Q_2week, Q_3week where Q_i is a dummy variable that takes 1 if the observation is from quarter i and 0 otherwise, week is a sequential tendency (1, 2, …,13) that represents the week index inside the quarter. By multiplying Q_i and $week$ the model estimates a different slope (tendency) for each quarter. The model estimated for the deterministic components (Q_i and week) indicates that the overall tendency is slightly positive (measured by week's coefficient), and both Q_1 and Q_2 have increasing quarterly trends, while Q_3 and Q_4 present negative ones.

Regarding the forecast, the following results were obtained:

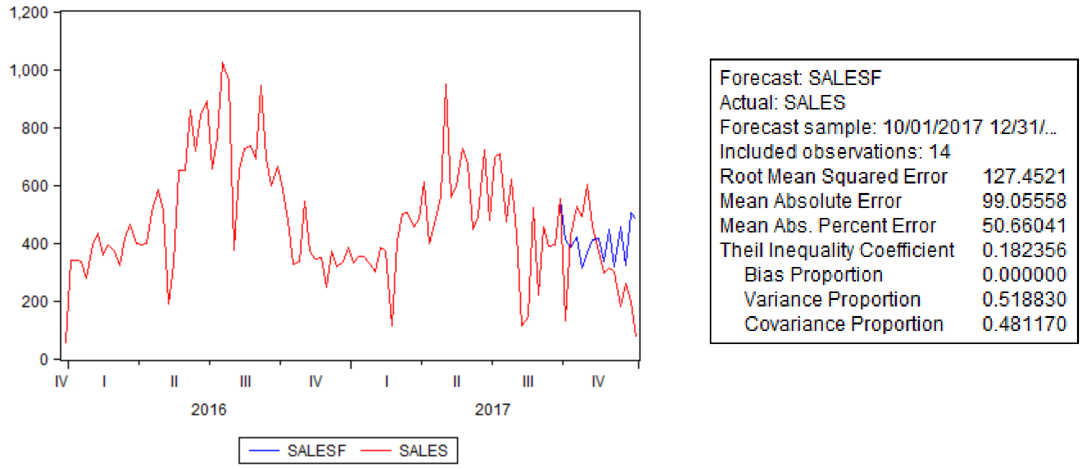


Figure 7: Forecast of the Sales of Take Home Ice Cream using ARIMA models

After comparing the forecast for the 4th quarter 2017 with the observed sales the following results were obtained (Figure 7): MAE = 99.05; RMSE = 127.45; MAPE = 50.66.

Also, other methods were analysed (see Appendix 8), however not as accurate as the model presented before, considering that simple moving average was calculated by:

$$F_t = \frac{Y_{t-1} + Y_{t-2} + \cdots + Y_{t-(t-1)}}{t-1} \quad (12)$$

where Y_t is the actual value.

The simple exponential smoothing was computed by

$$F_t = \mathrm{F_{t-1}} + \alpha\,(\mathrm{Y_{t-1}} - \mathrm{F_{t-1}}) \tag{13}$$

where $\mathrm{F_{t-1}}$ represents the last forecast value and α was calculated according to solver function in Excel, in order to minimise the MSE. α represents the smoothing constant ($0< \alpha <1$). The estimated α was 0.5481.

Note that the current forecasting method of the company is based on the simple moving average of the last four weeks of the current year ($F_t = \frac{Y_{t-1}+Y_{t-2}+\cdots+Y_{t-4}}{4}$). However, this value is updated, using a multiplicative seasonal index, according to corresponding the average of the last four weeks of the last year:

$$F'_t = F_t * I_t \tag{14}$$

In conclusion, it was possible to notice that the current company's forecasting method was not as accurate as other calculated methods since it showed higher MSE and RMSE, therefore the company should consider other methods to improve its forecasts (Table 5).

Table 5: Analysis of forecasting methods of the Take Home Ice Cream subcategory – MSE and RMSE for the 4th quarter of 2017.

Forecasting methods for Sales of Ice Cream	**Simple moving average (1 week)**	**Simple moving average (2 weeks)**	**Simple moving average (3 weeks)**	**Simple moving average (4 weeks)**	**Simple moving average (5 weeks)**	**Simple exponential smoothing**	**Company's forecasting method**
MSE for 4th quarter 2017	25,594.79	20,079.18	18,500.05	21,460.72	20,213.26	19,197.40	23,074.20
RMSE for 4th quarter 2017	159.98	141.70	136.01	146.49	142.17	138.55	151.90

Note: The yellow numbers represent the best method with the best result, which is the lower MSE and RMSE.

7.4- FORECASTING METHODS USING AN ADJUSTMENT OF PROMOTIONS

The current forecasting method of the company consists in using the historical data of sales without counting sales of promoted products. However, by eliminating all the sales of products that were in promotion at that time, the company is not accounting the sales that products would have had if they were not in promotion. The company's forecast is, thus, wrongly affected by the cannibalisation of the sales due to promotions, and a week of higher sales of promoted products will usually correspond to a week of lower sales of non-promoted products due to the cannibalisation of the promotion. Thus, the company will not include a significant amount of sales in its historical data in those weeks, as the company is just considering the sales without promotions.

To prove that the company would have better results, i.e lower MSE of its forecasting methods, an adjustment of the historical observed values of the subcategory of Take Home Ice Cream was organized. That adjustment consisted in changing the historical sales of non-promoted products to an estimated value according to the following steps (see Appendix 9 for a detailed description of this adjustment):

1- Assess if the proportion of sales of promoted products in the total sales of the subcategory (sales with and without promotions) is higher than 60% in a specific week, in which case there is the need to adjust the sales value of that week: $\frac{Sales_{with\ promo}}{Sales_{total\ sales}} > 60\%$. (Note: the value 60% was used as an experimental value, and future research might be conducted to identify the best value to be used).
2- Use the values of the sales without promotions for the forecast of future sales.
3- Modify the values of sales without promotions of the weeks that need to be changed, see step 1 above. The value is modified by the average of the last four weeks of sales without promotions: $Sales_{\ t} = \frac{Sales_{t-1}+Sales_{t-2}+Sales_{t-3}+Sales_{(t-4)}}{4}$.

Previous methods, simple moving average, simple exponential smoothing and the current ABC company's forecasting method were calculated using this adjustment of promotions to test its precision (see Appendix 10). The results showed that the company could improve its forecasts by using this adjustment since MSE and RMSE of the forecasting methods studied, for the last quarter of 2017, were lower, as represented in yellow in Table 6. The estimated α for simple exponential smoothing used was 0.6867.

Table 6: Analysis of forecasting methods of the Adjusted Take Home Ice Cream Sales for Promotions – MSE and RMSE for the 4th quarter of 2017.

Forecasting methods - Adjustment of Promotions (Sales of Ice Cream)	**Simple moving average (1 week)**	**Simple moving average (2 weeks)**	**Simple moving average (3 weeks)**	**Simple moving average (4 weeks)**	**Simple moving average (5 weeks)**	**Simple exponential smoothing**	**Company's forecasting method**
MSE for 4th quarter 2017	4,052.71	4,348.89	5,544.73	6,644.77	7,500.7	4,035.69	9,318.92
RMSE for 4th quarter 2017	63.66	65.95	74.46	81.52	86.61	63.53	96.53

8- CONCLUSIONS AND LIMITATIONS

The study found some constant patterns of existence of seasonality, comparing the two years analysed, such as: ice cream has higher consumption in the Spring and Summer and laundry detergent pod usually has an increase of sales during the first and last week of the month.

Promotions can cannibalise similar products of the ABC company. It was verified that if a promotion of a certain product occurs, the sales of that product will increase, however that increase is more evident in the first week of the promotion than in the following ones if the promotion lasts more than one week. There is a decrease in sales of a specific product, if other similar or substitute products were on promotion, and again the impact is more visible in the first week. The sales of the company were highly influenced by promotions and this was more evident with the formula:

$$Y_t = \frac{Y_{t-1}+Y_{t-2}+Y_{t-3}+Y_{t-4}}{4} + effect\ of\ the\ promotion \qquad (15)$$

With this formula, it was concluded that sales of some products, such as deodorants and laundry detergent pods, were very impacted by promotions.

Then, an analysis of forecasting methods was conducted. The subcategory for this analysis chosen was Take Home Ice Cream. The ARIMA model was estimated, using Box-Jenkins approach. Other three methods were used: simple moving average, simple exponential smoothing and the current forecasting method of the company. The ARIMA model showed the best results. The current forecasting method of the company was not the most precise, compared to other methods. Therefore, the company should review its forecasting methodology in order to achieve better forecasting accuracy.

The company is only counting sales of products that are not in promotion, and that affects the accuracy of forecasts. There is a significant cannibalisation when promoted products substitute products without promotion, which the company is not taking into consideration. Thus, an adjustment was created to overcome this issue, which led the company forecasts to show lower error and more accuracy. Therefore, the company should consider this adjustment in the future.

For forecasting purposes, the ABC company only relies on historical data and not on other relevant factors, such as the competitors' prices, cannibalisation and halo effects, market and industry new trends and social media influence. Thus, in a future research, the company might align these new trends and effects and create a more complete forecasting system.

Concerning the limitations of the present work, owing to a lack of information provided by the company, it was not possible to determine what errors the MRP tool is actually doing, nor to compare the real forecasting of the company with the actual sales. This lack of information was due to the fact that the company does not store its last forecasts or orders in the system. For a more accurate analysis, the company should invest in more information space, even implying more expenditures. Indeed, the company could benefit from historical data to be able to proper understand its current forecasting errors and to set new strategies in order to mitigate and control these errors.

Another limitation of this analysis was not being possible to use forecasting methods that account for seasonality, such as SARIMA models, due to the short period of the data provided (two years).

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10- APPENDICES

APPENDIX 1 – ANALYSIS OF STOCK OUTS

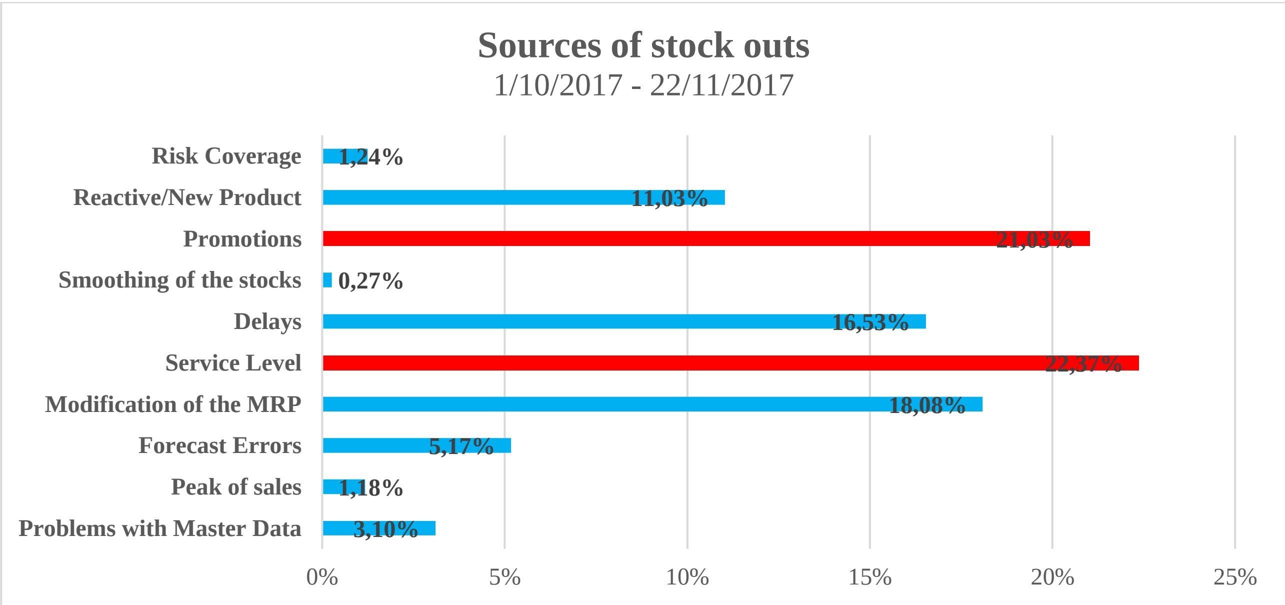


Figure 1: Sources of stock outs

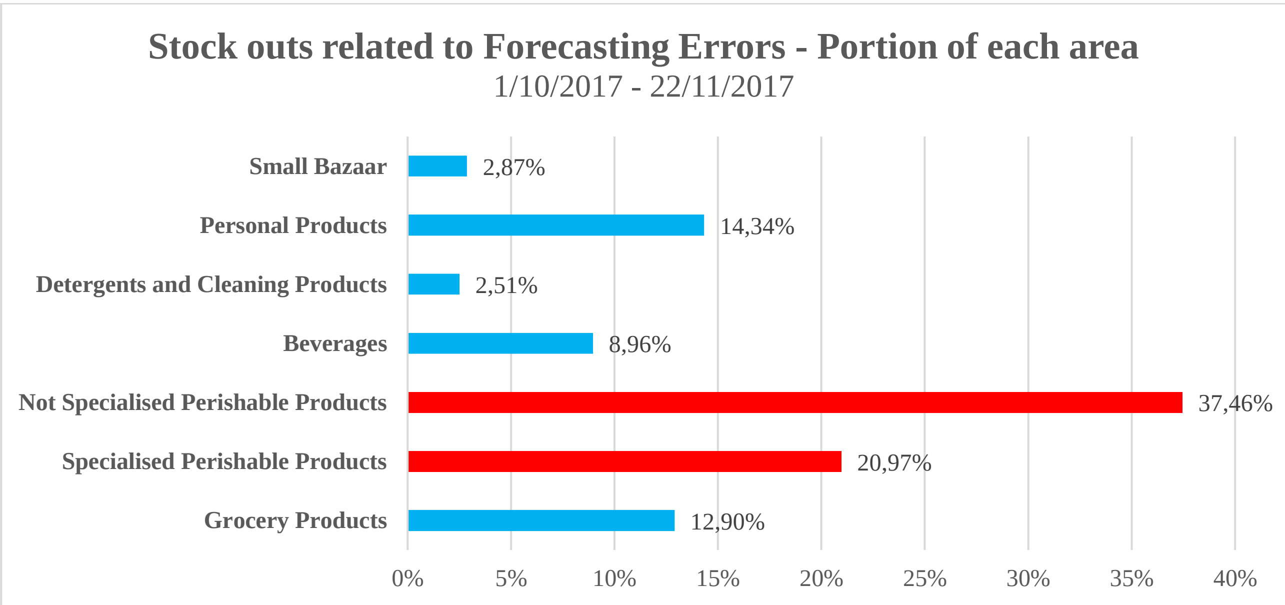


Figure 2: Stock outs related to Forecasting Errors - Portion of each area (1/10/2017 - 22/11/2017)

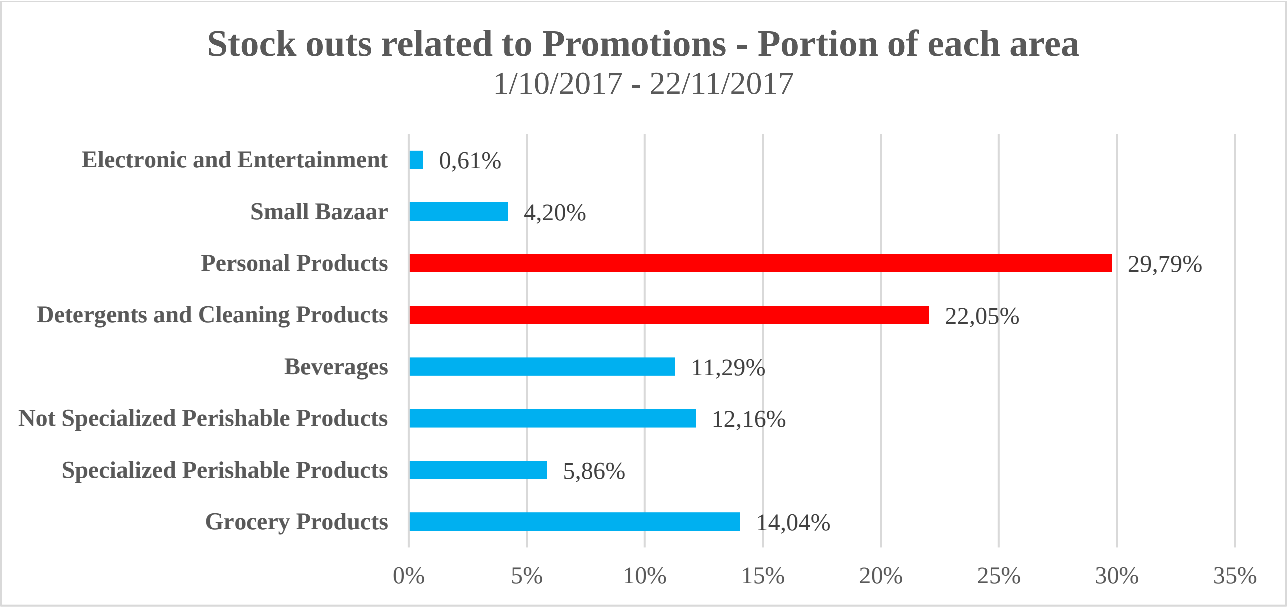


Figure 3: Stock outs related to Promotions - Portion of each area (1/10/2017 - 22/11/2017)

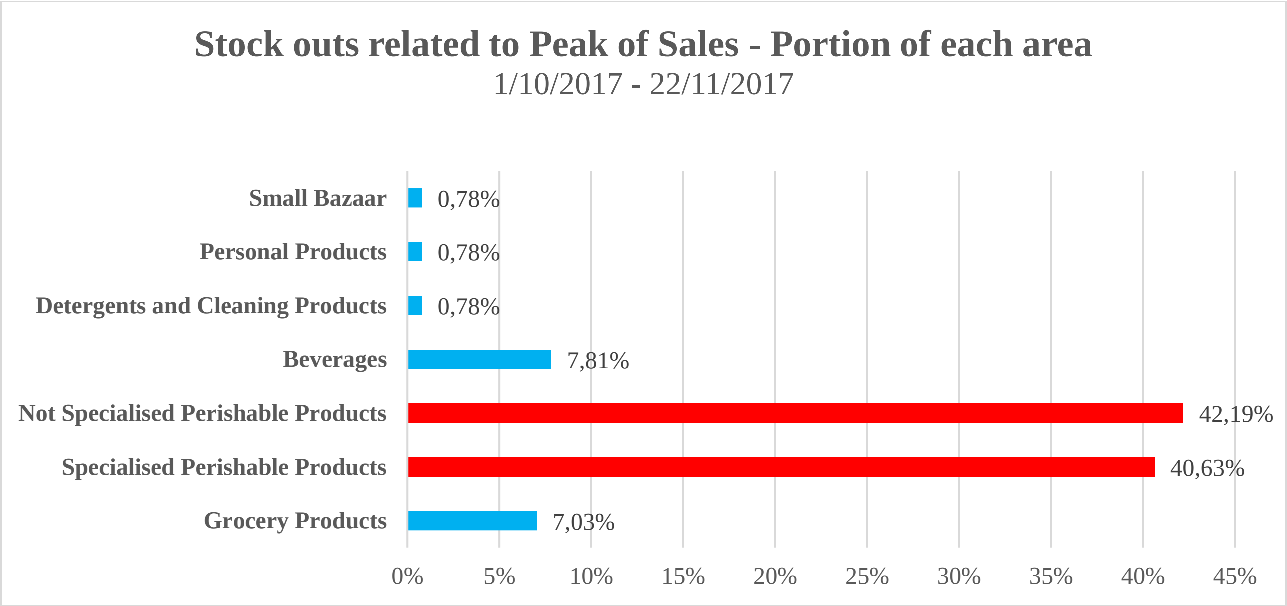


Figure 4: Stock outs related to Peak of Sales - Portion of each area (1/10/2017 - 22/11/2017)

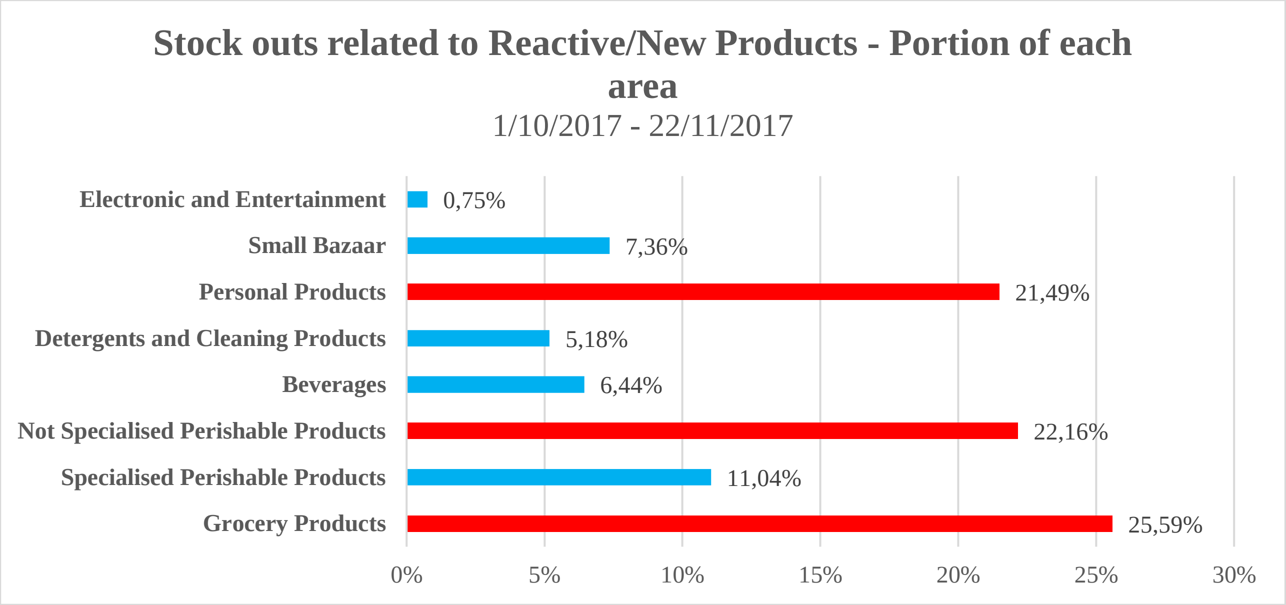


Figure 5: Stock outs related to Reactive/New Products - Portion of each area (1/10/2017 - 22/11/2017)

APPENDIX 2 – IMPACT OF SEASONALITY

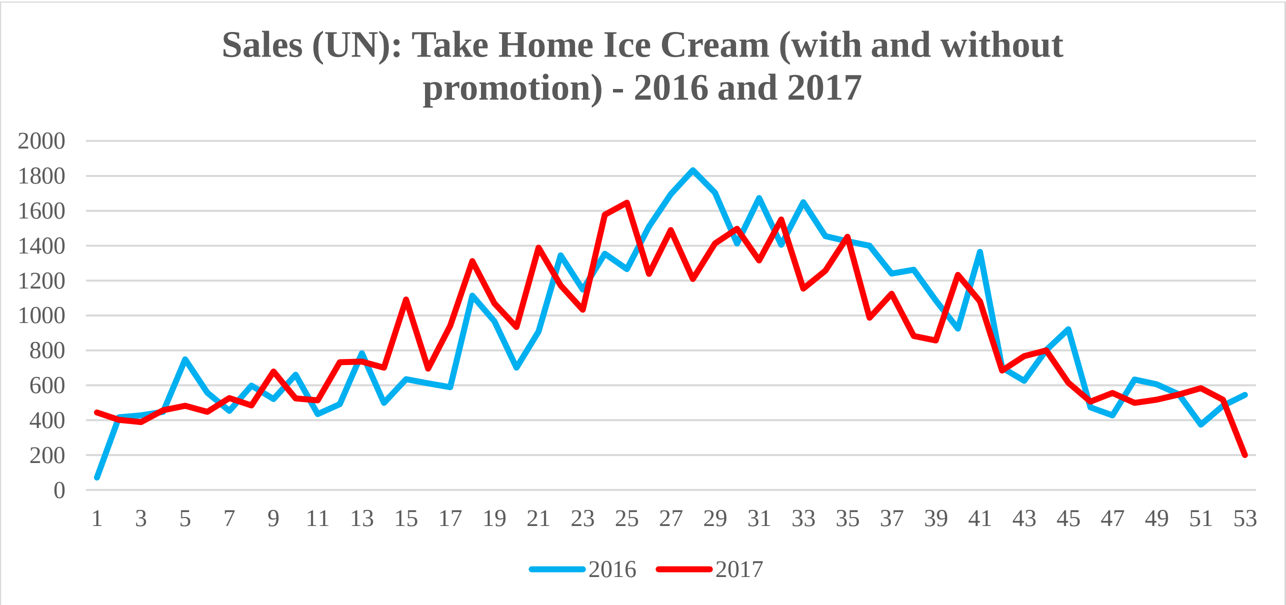


Figure 1: Sales (UN): Take Home Ice Cream (with and without promotion) - 2016 and 2017

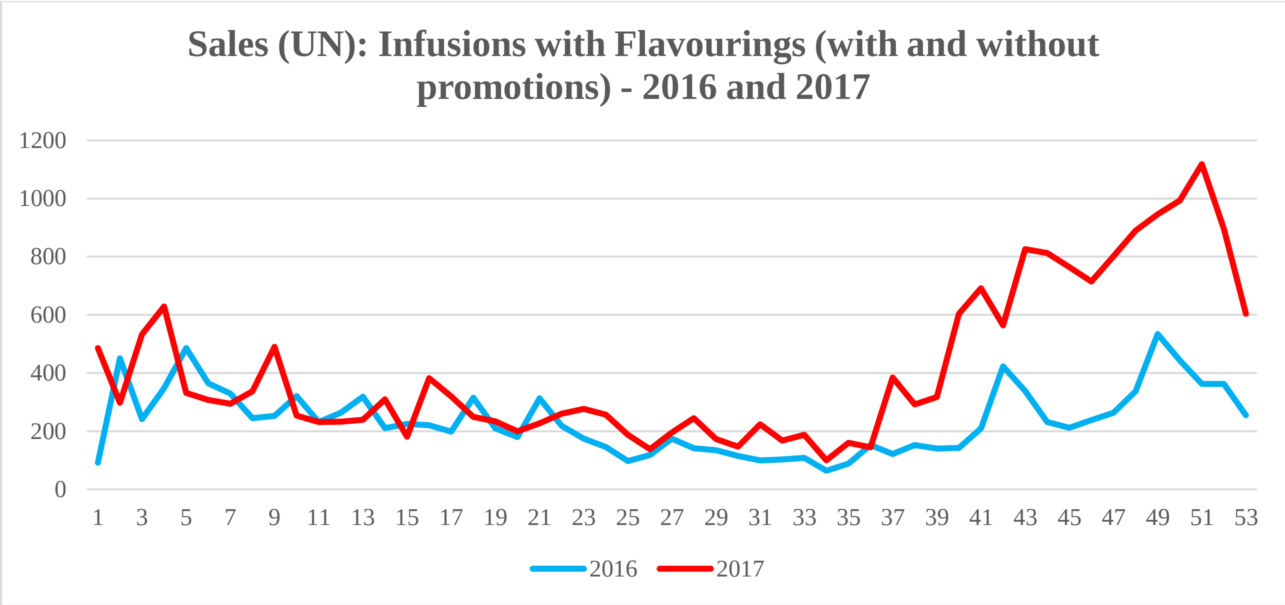


Figure 2: Sales (UN): Infusions with Flavourings (with and without promotions) - 2016 and 2017

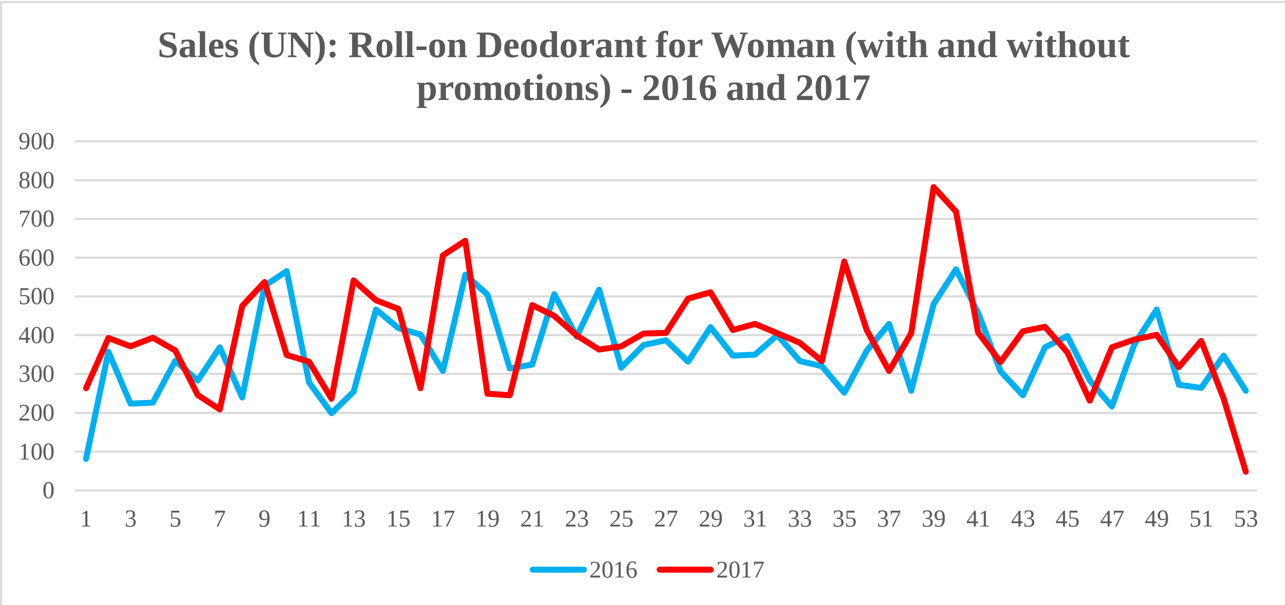


Figure 3: Sales (UN): Roll-on Deodorant for Woman (with and without promotions) - 2016 and 2017

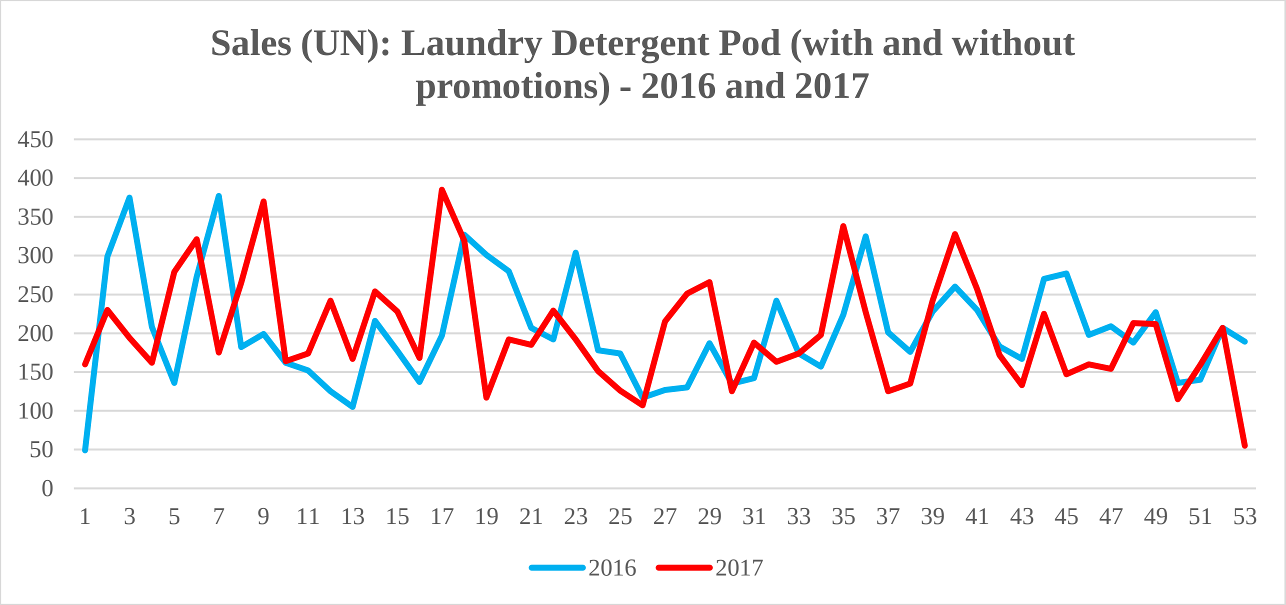


Figure 4: Sales (UN): Laundry Detergent Pod (with and without promotions) - 2016 and 2017

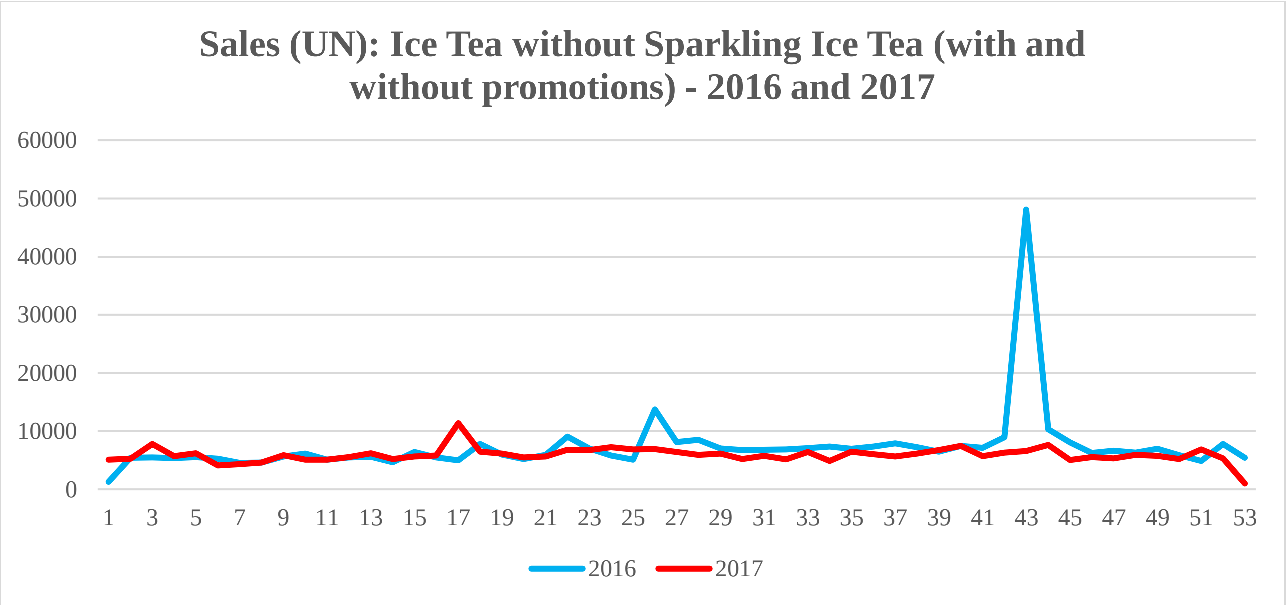


Figure 5: Sales (UN): Ice Tea without Sparkling Ice Tea (with and without promotions) - 2016 and 2017

APPENDIX 3 – IMPACT OF SEASONALITY - PRODUCTS WITHOUT PROMOTIONS

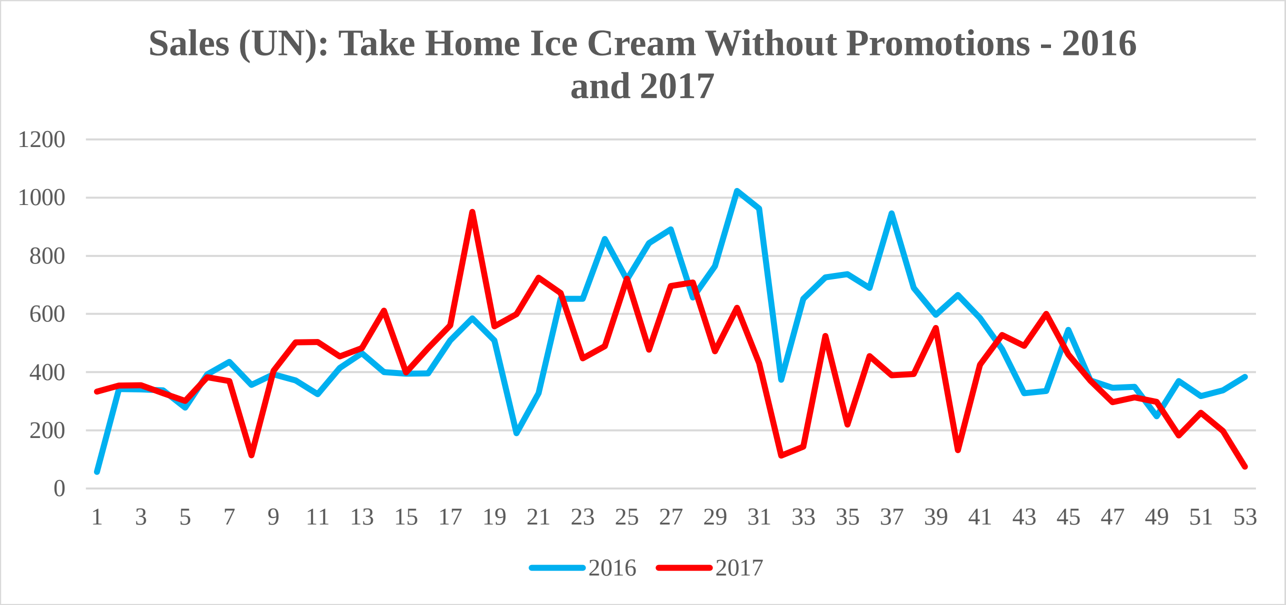


Figure 1: Sales (UN): Take Home Ice Cream Without Promotions - 2016 and 2017

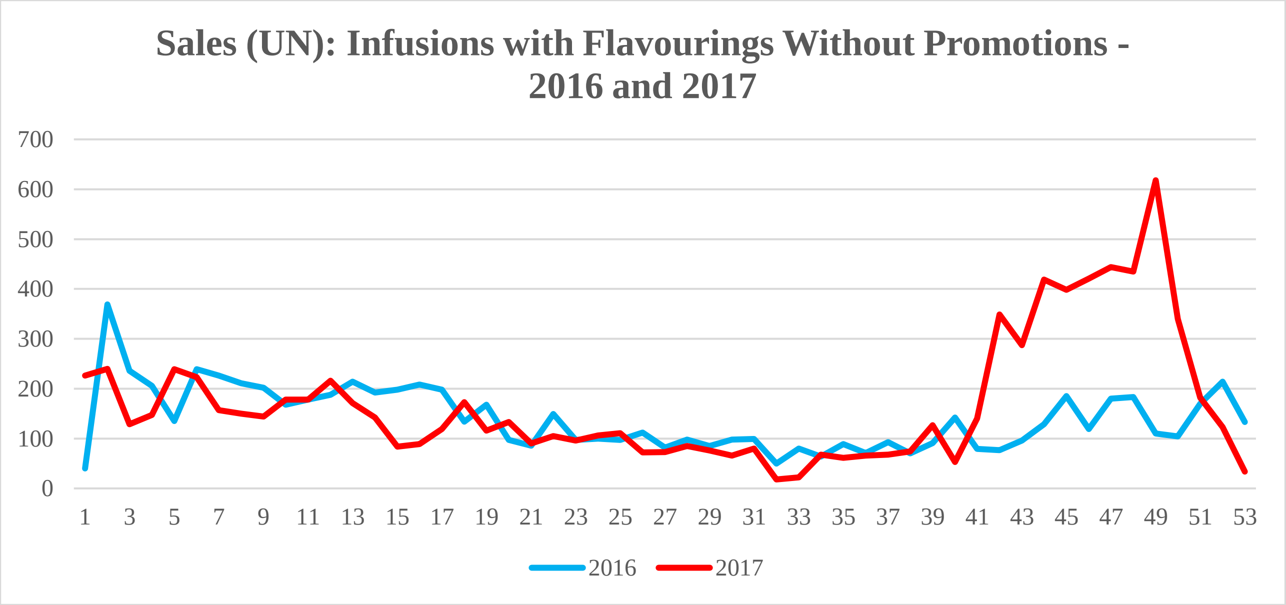


Figure 2: Sales (UN): Infusions with Flavourings Without Promotions - 2016 and 2017

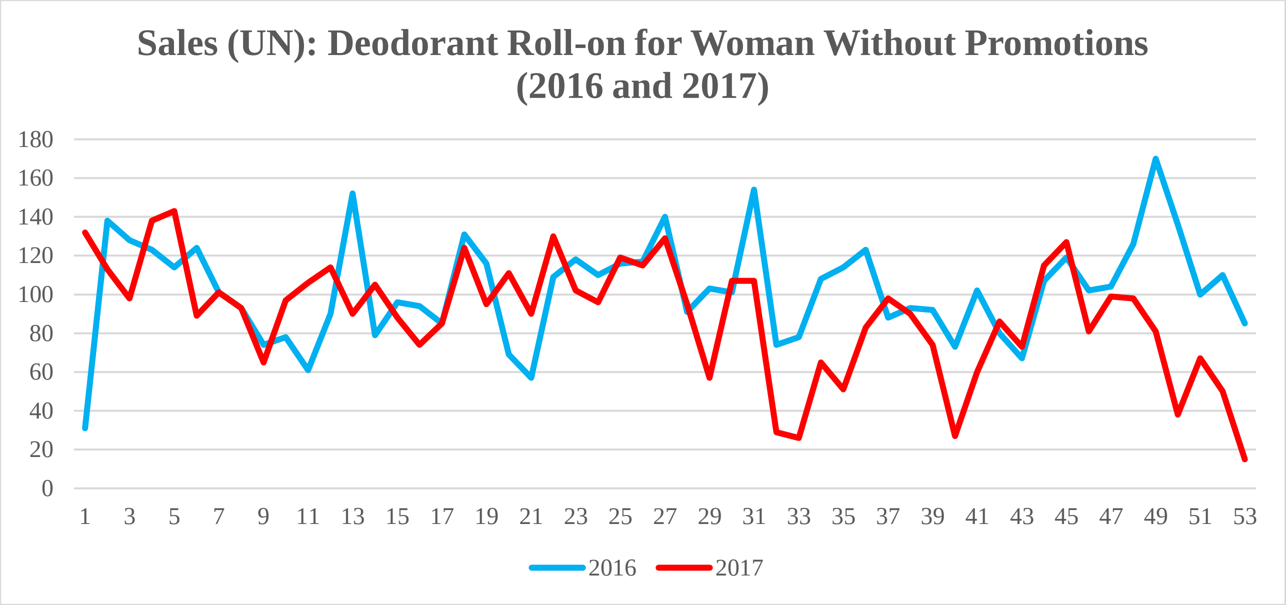


Figure 3: Sales (UN): Deodorant Roll-on for Woman Without Promotions (2016 and 2017)

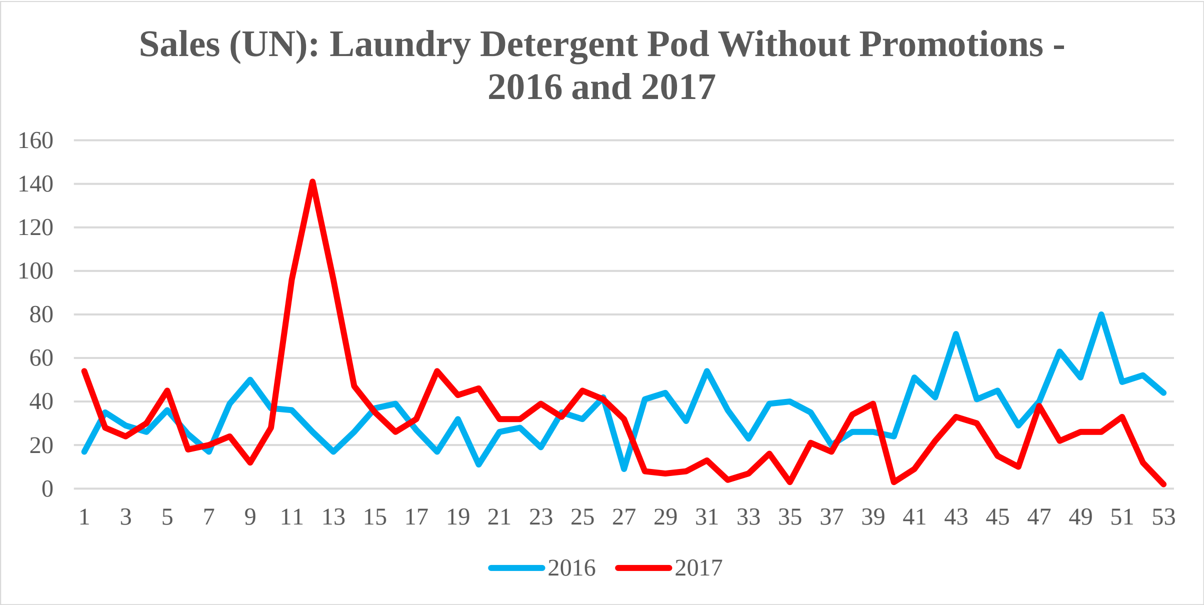


Figure 4: Sales (UN): Laundry Detergent Pod Without Promotions - 2016 and 2017

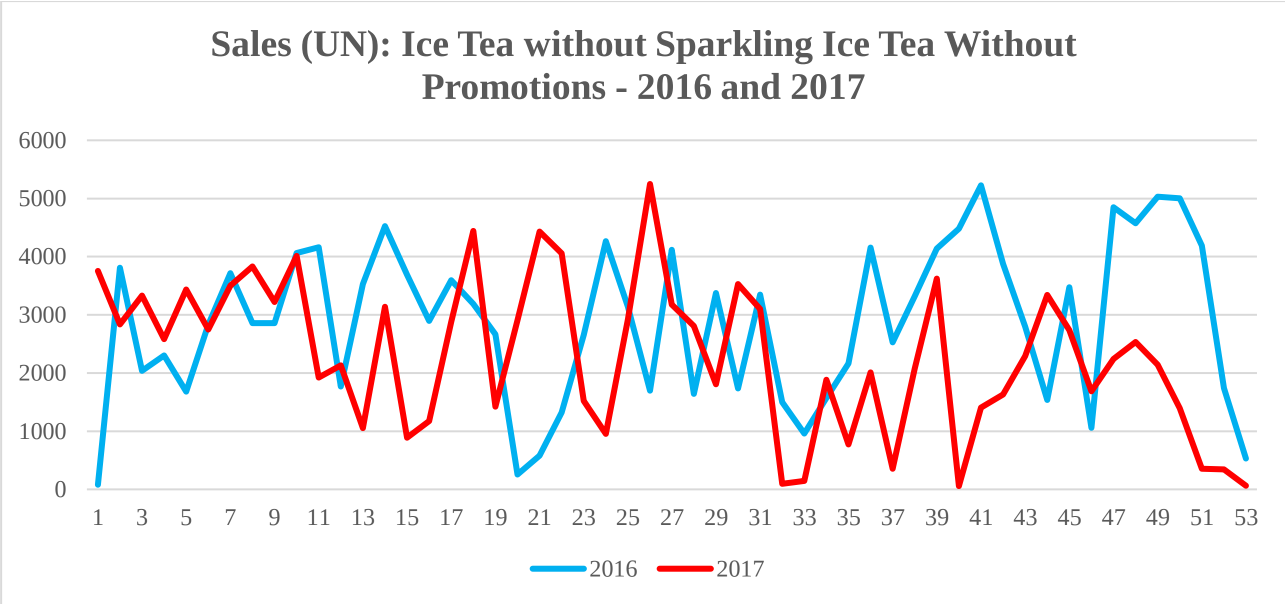


Figure 5: Sales (UN): Ice Tea without Sparkling Ice Tea Without Promotions - 2016 and 2017

APPENDIX 4 – IMPACT OF SEASONALITY– SALES AND NUMBER OF TRANSACTIONS

1) SALES EVALUATION

- OTHER BRANDS

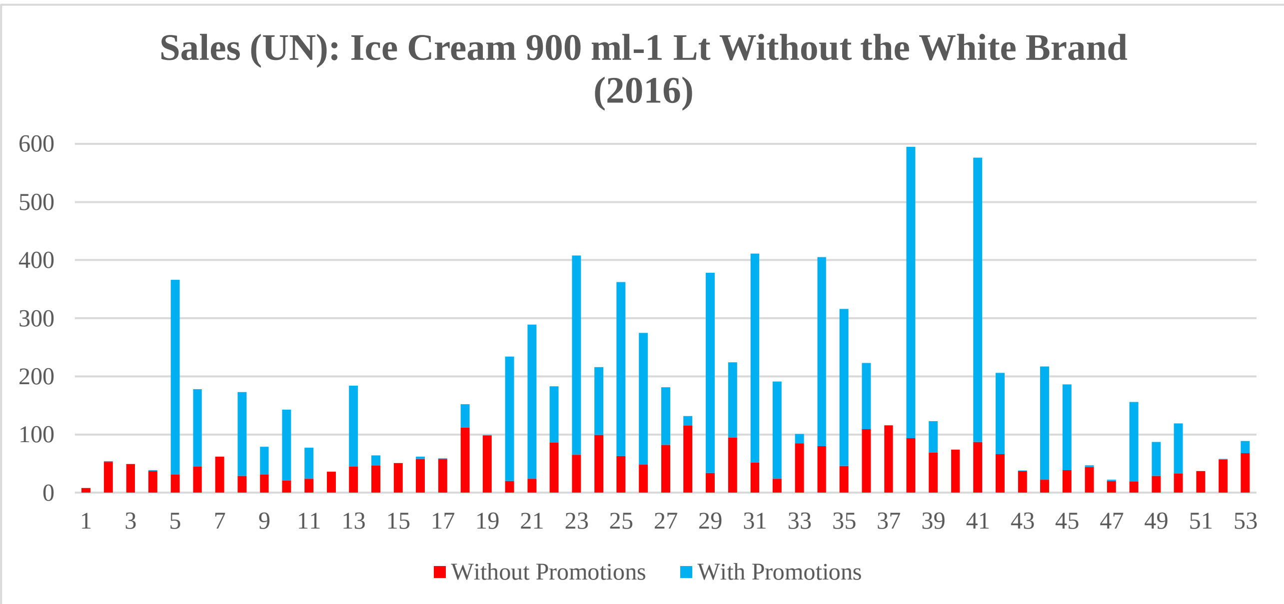


Figure 1: Sales (UN): Ice Cream 900 ml-1 Lt Without the White Brand (2016)

Conclusions: Higher number of sales in the spring and summer, from May until September. The promotions had influence in the purchase.

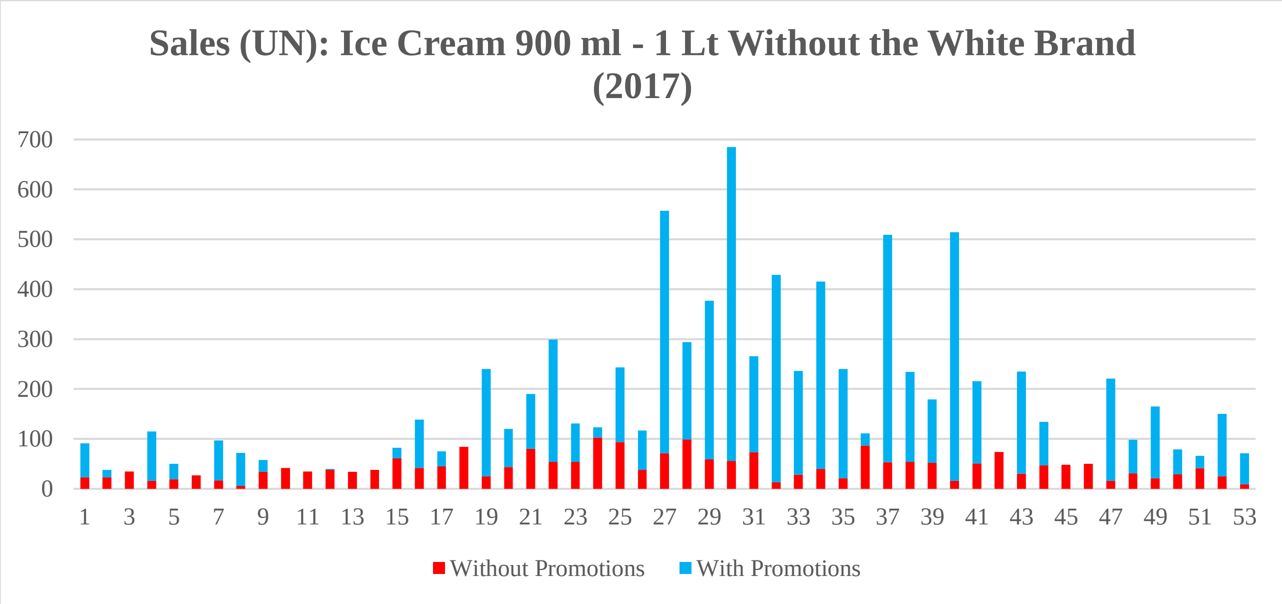


Figure 2: Sales (UN): Ice Cream 900 ml - 1 Lt Without the White Brand (2017)

Conclusions: Higher quantity of sales in the summer, from June until September. Promotions of ice cream had a higher impact in 2017 than 2016.

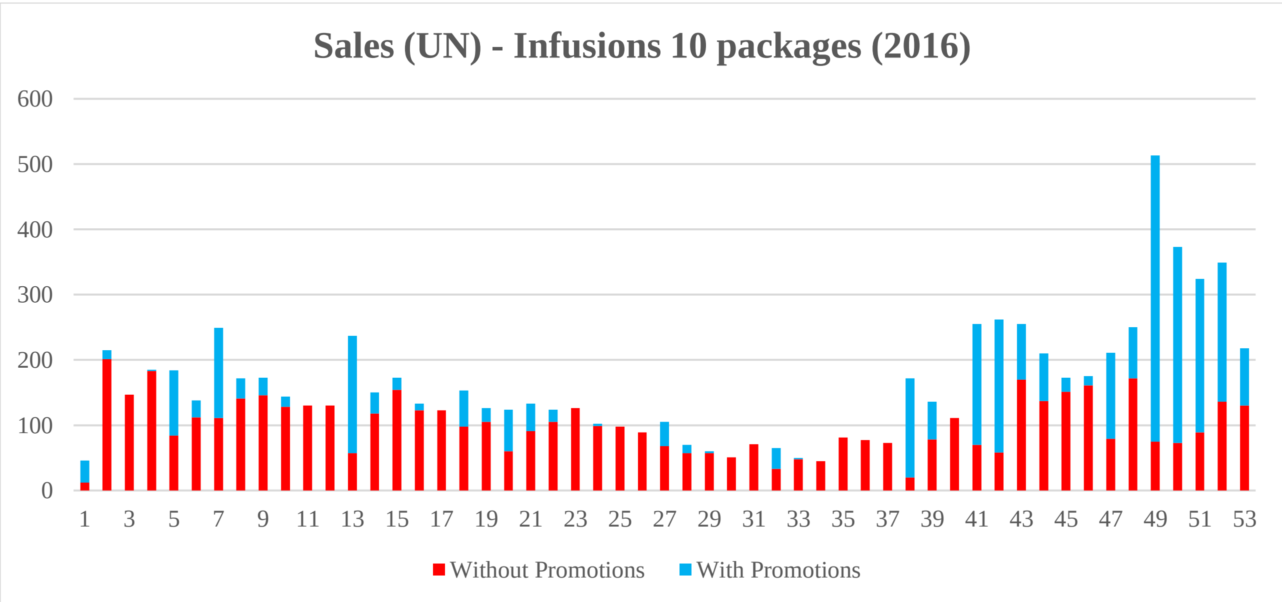


Figure 3: Sales (UN) - Infusions 10 packages (2016)

Conclusions: In 2016 the sales of infusions with promotions did not have much impact on the total sales. It is possible to denote higher sales in the months from September until December. Considering also that promotions had more impact in these months.

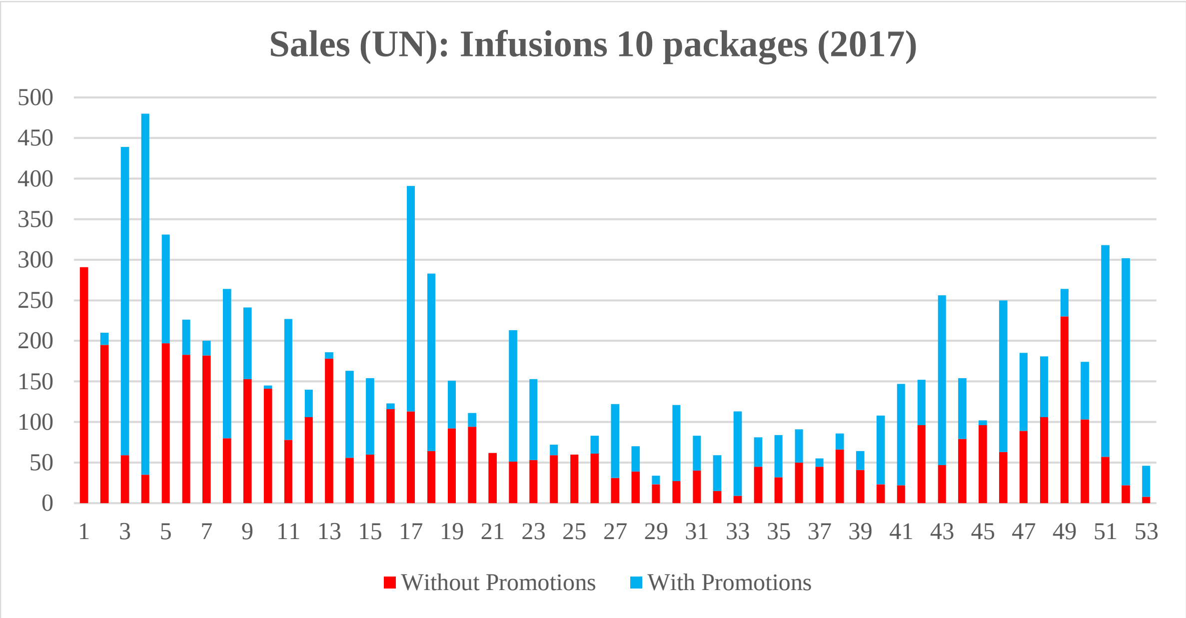


Figure 4: Sales (UN): Infusions 10 packages (2017)

Conclusions: The sale of infusions denoted higher values in the months of winter, from January until April and from October until December. In the months of winter, the promotions had more impact than the months of other seasons.

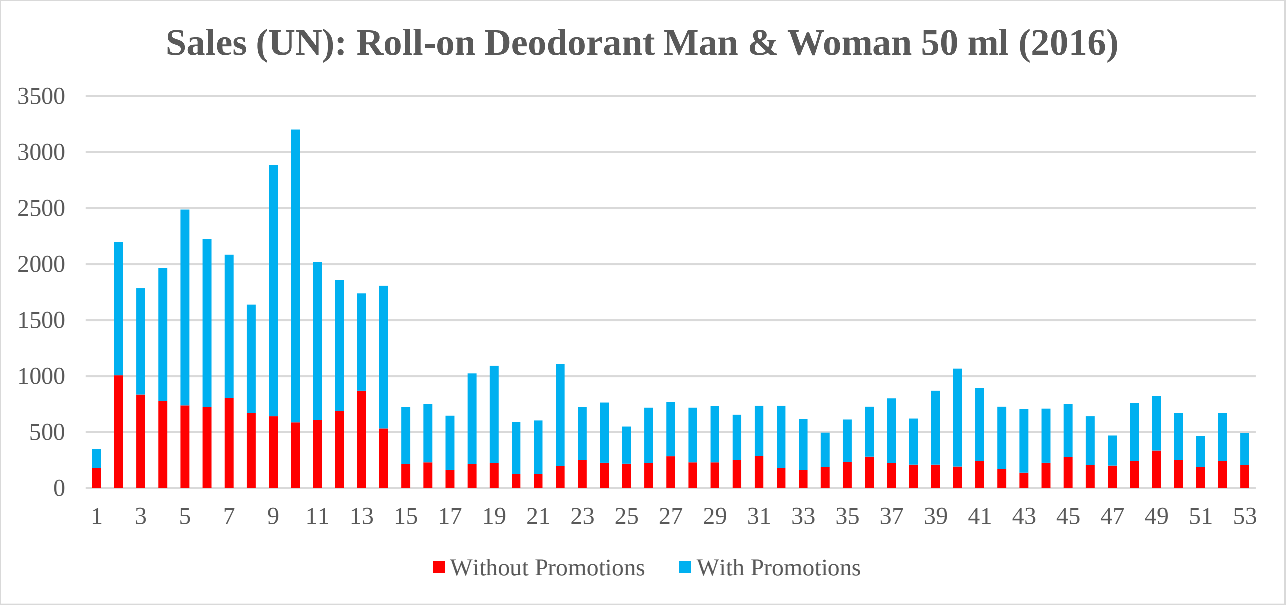


Figure 5: Sales (UN): Roll-on Deodorant Man & Woman 50 ml (2016)

Conclusions: Promotions showed a strong influence in the purchase of roll-on deodorants. It is possible to a higher number of sales during the months of January, February and March. The sales of deodorants had the tendency to be higher during the last week of the month throughout the year.

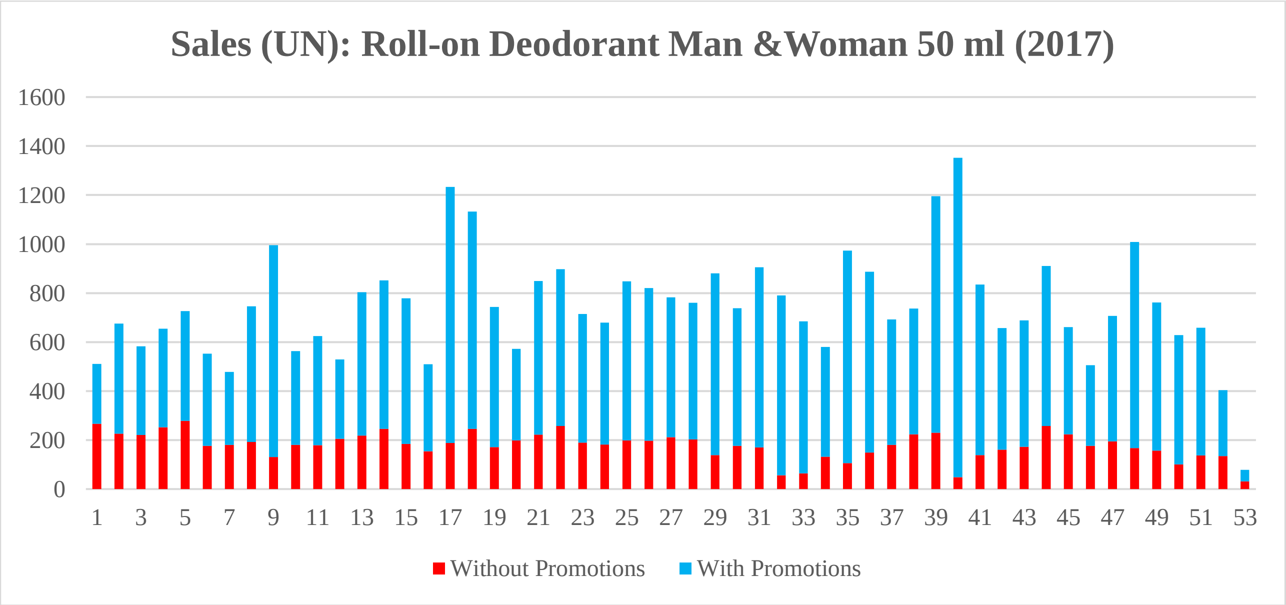


Figure 6: Sales (UN): Roll-on Deodorant Man &Woman 50 ml (2017)

Conclusions: In 2017, there was a regular consumption of this product throughout the year. However, it is possible to conclude the higher influence of the promotions in the total sales of this specific product. The highest number of sales coincides with the last week of the month, this was verified in most of the months throughout the year.

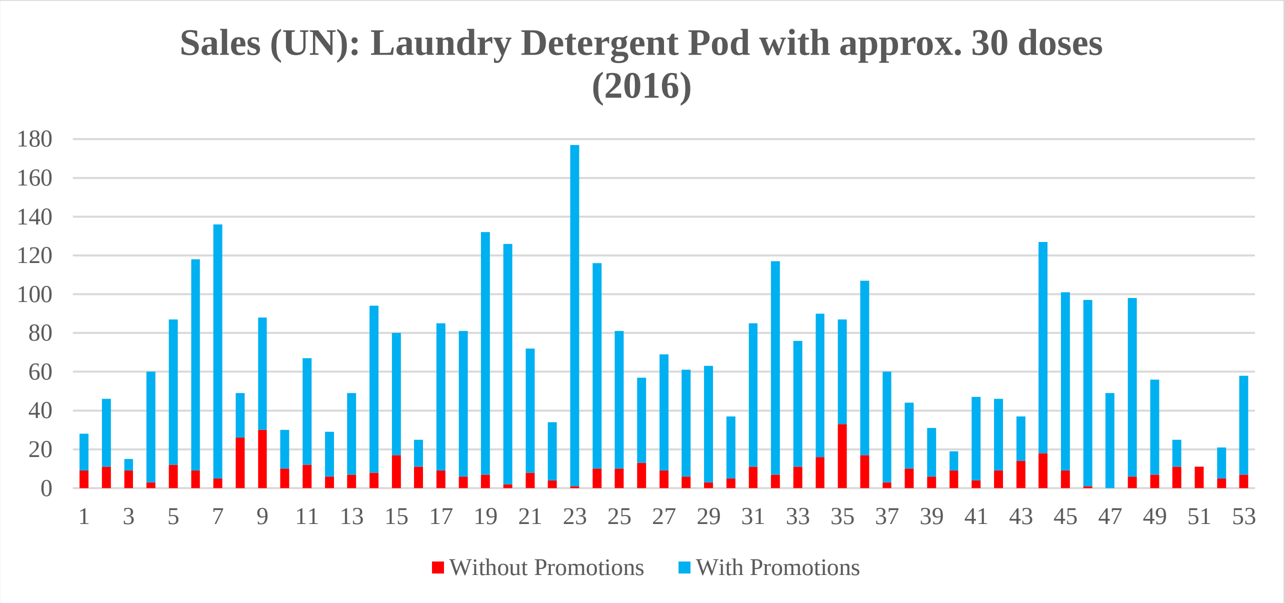


Figure 7: Sales (UN): Laundry Detergent Pod with approx. 30 doses (2016)

Conclusions: Regarding the laundry detergent pod, a regular pattern of sales during the year was possible to denote, however customers tend to buy more in the beginning of the month and in the end of the month. The impact of the promotions on the total sales of the laundry detergent pod is high.

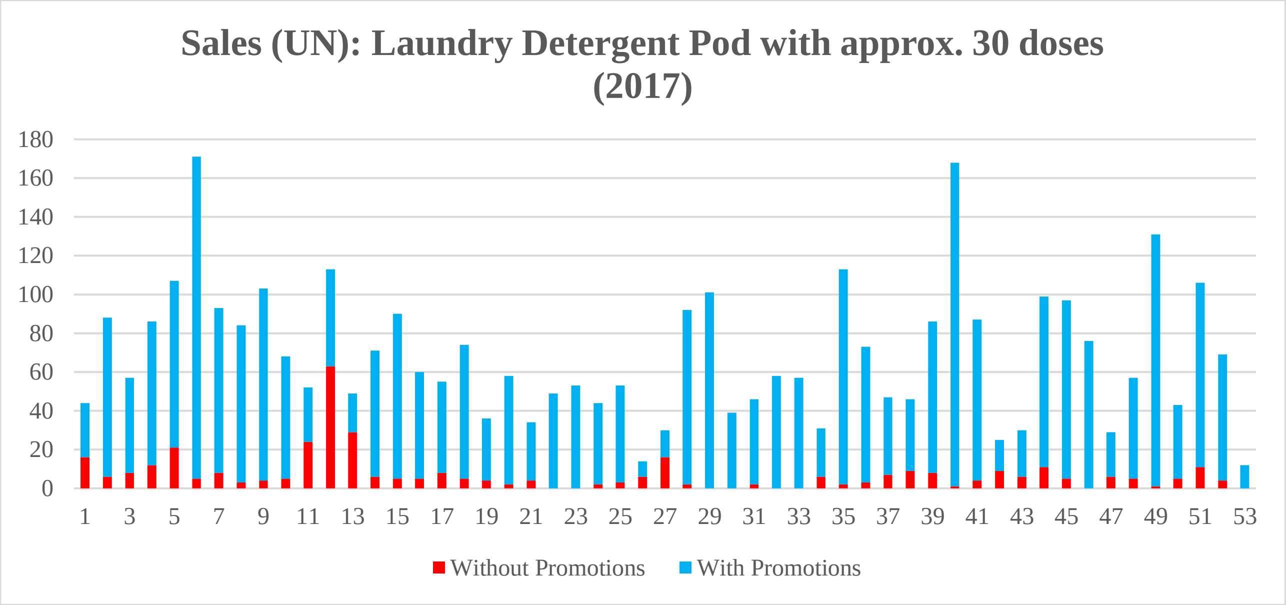


Figure 8: Sales (UN): Laundry Detergent Pod with approx. 30 doses (2017)

Conclusions: Similar pattern throughout the year in what concerns the sales of laundry detergent pod. High impact of the promotions on the total sales of laundry detergent pod.

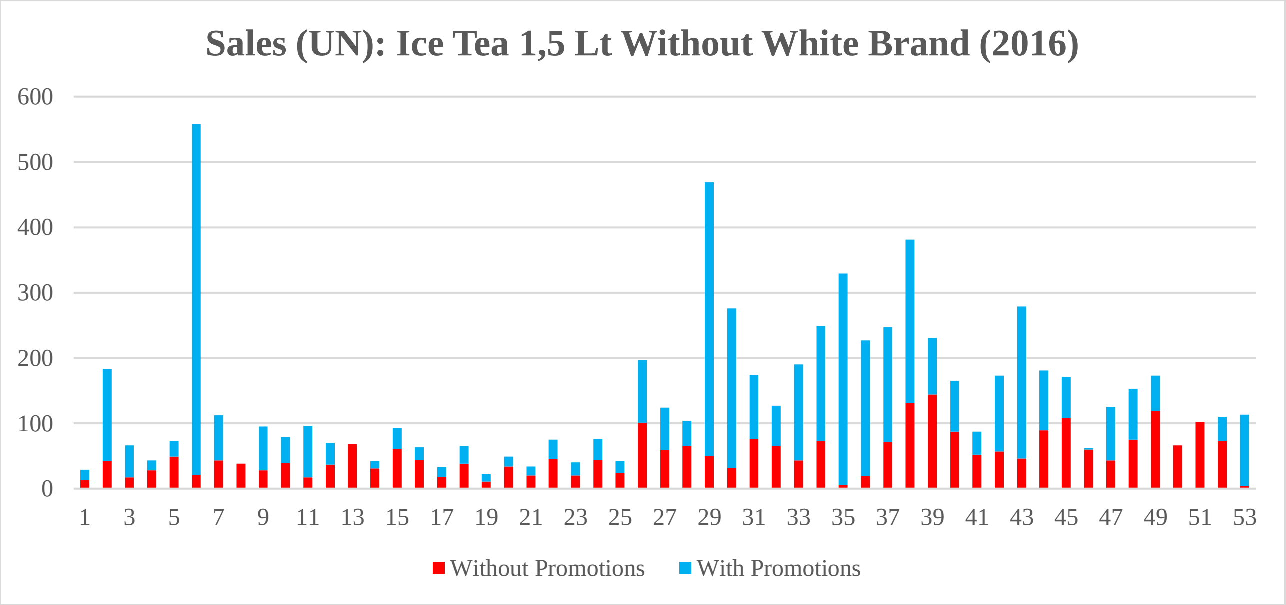


Figure 9: Sales (UN): Ice Tea 1,5 Lt Without White Brand (2016)

Conclusions: Higher consumption levels from July until October. The impact of promotions was still considerable and they can cause more impact during the months with higher consumption.

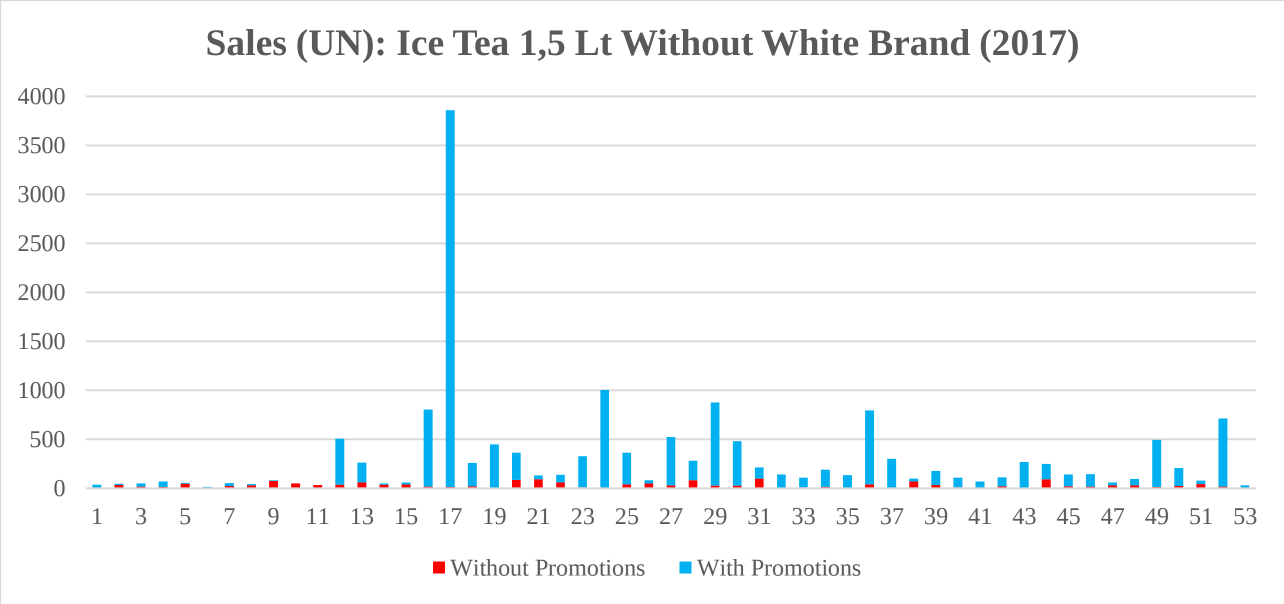


Figure 10: Sales (UN): Ice Tea 1,5 Lt Without White Brand (2017)

Conclusions: Ice Tea without white brand with promotion has more sales than without promotion. It is possible also to denote a higher value of sales in the Easter's week.

- ABC COMPANY'S WHITE BRAND

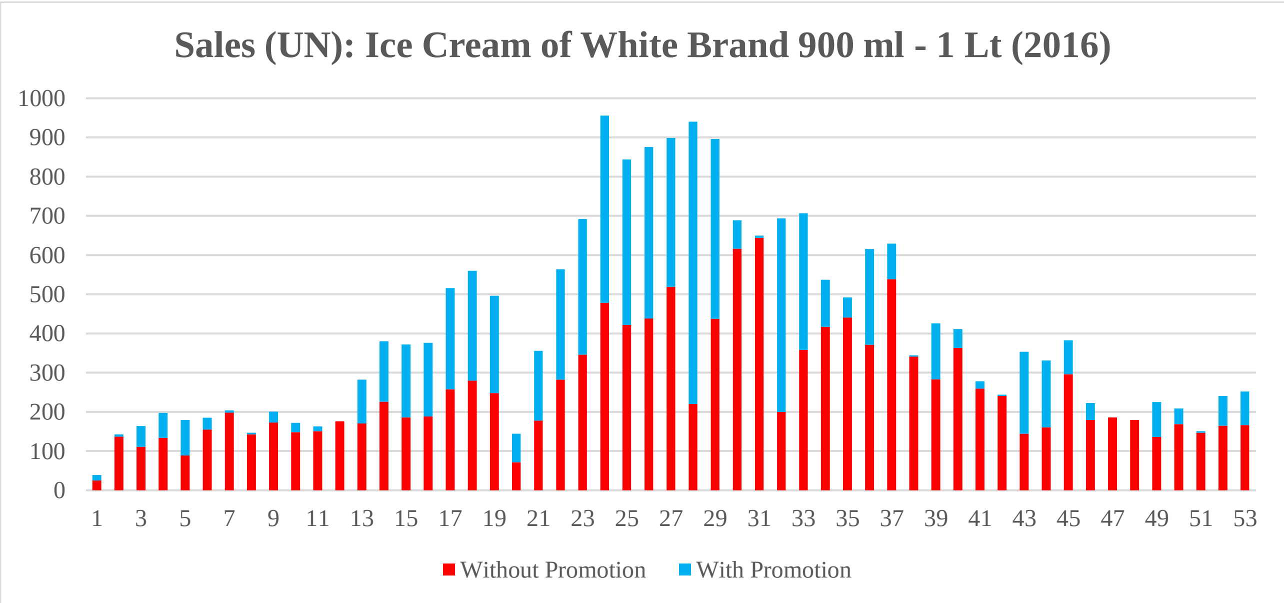


Figure 11: Sales (UN): Ice Cream of White Brand 900 ml - 1 Lt (2016)

Conclusions: Higher quantities of sales in the summer, from June until August. The white brand had a substantial portion in the total ice cream's sales. The promotions of the white brand did not have much impact in the purchase of this product.

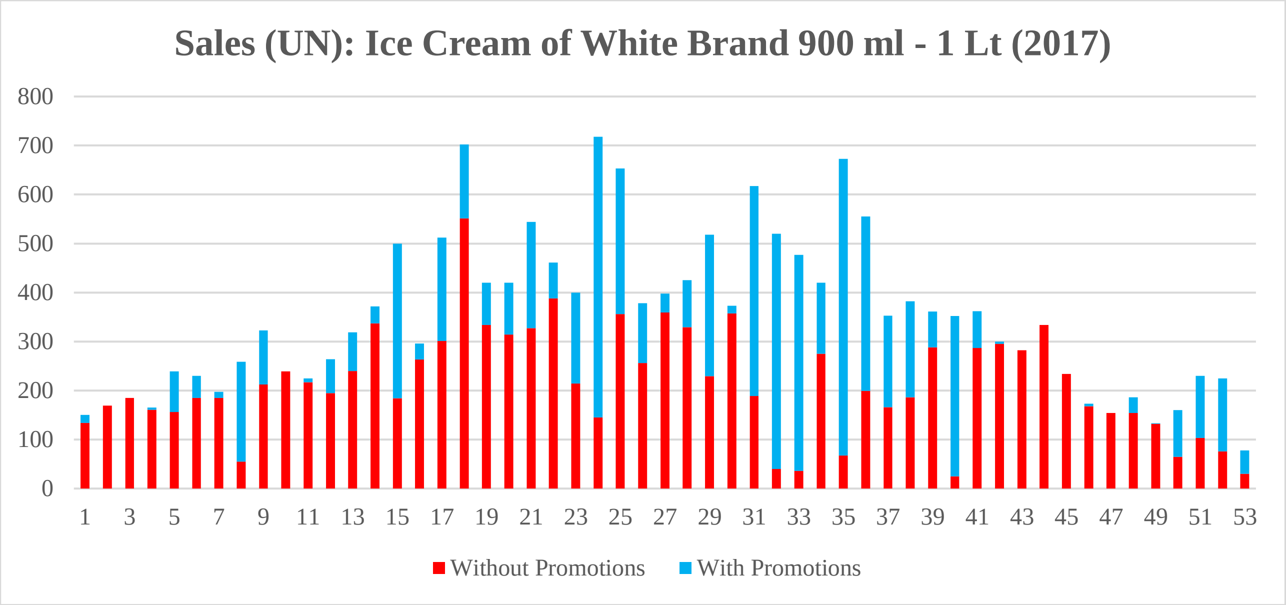


Figure 12: Sales (UN): Ice Cream of White Brand 900 ml - 1 Lt (2017)

Conclusions: The white brand's ice cream in 2017 had a more constant number of sales during the year, even though it is possible to denote higher sales in the spring and summer, from May until September. Moreover, there was a higher number of sales of white brand's ice cream without promotions.

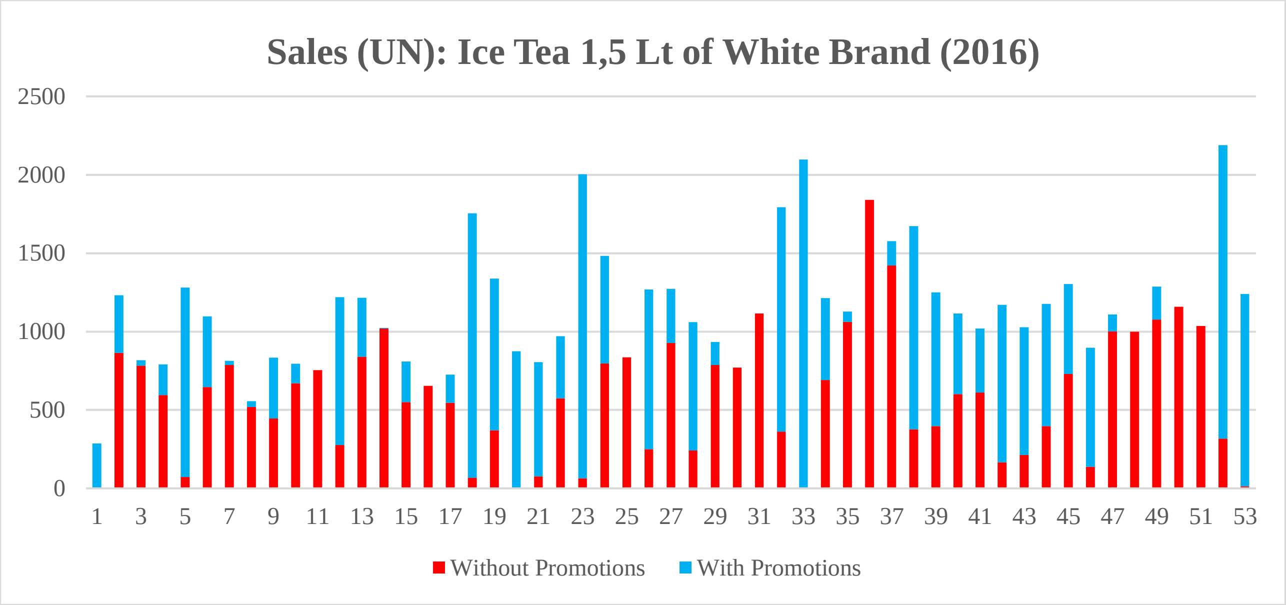


Figure 13: Sales (UN): Ice Tea 1,5 Lt of White Brand (2016)

Conclusions: The sales of ABC company's white brand were constant during the year. Furthermore, the promotions did not impact much the sales of ice tea white brand, only in some occasions in the months April, May, August and December, coinciding in some ceremonial events, such as Easter and Christmas

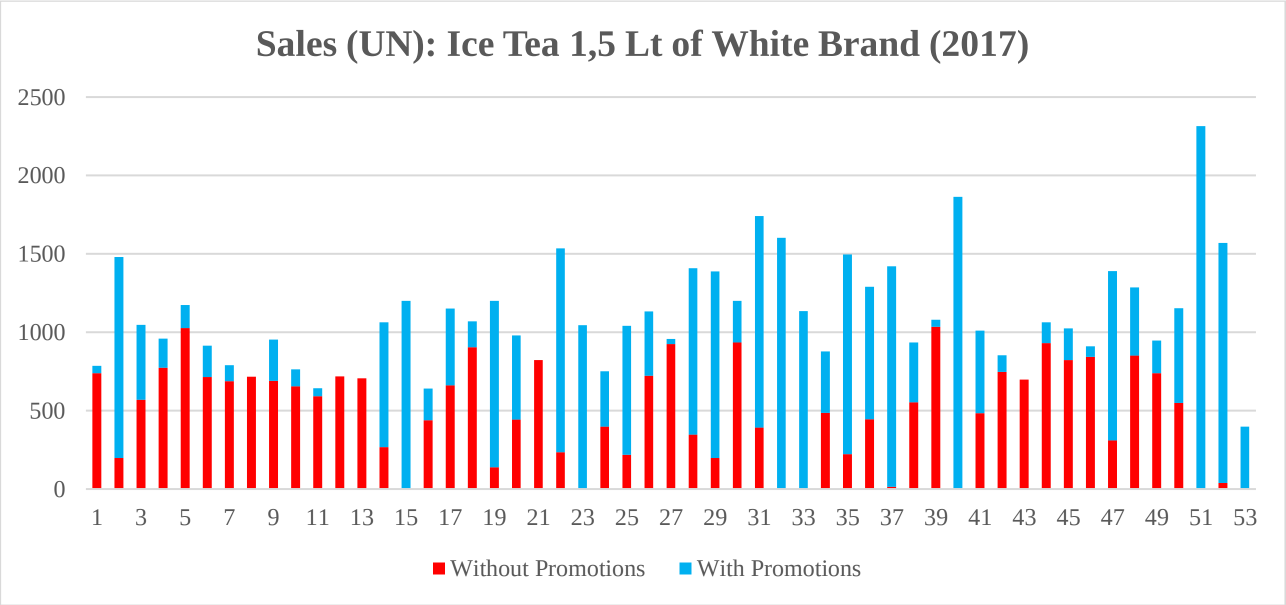


Figure 14: Sales (UN): Ice Tea 1,5 Lt of White Brand (2017)

Conclusions: The ABC company's white brand of ice tea had a constant amount of sales during the whole year. The promotions had some impact on the sales, however there was still a considerable amount of sales of white brand without promotions.

2) NUMBER OF TRANSACTIONS EVALUATION

- OTHER BRANDS

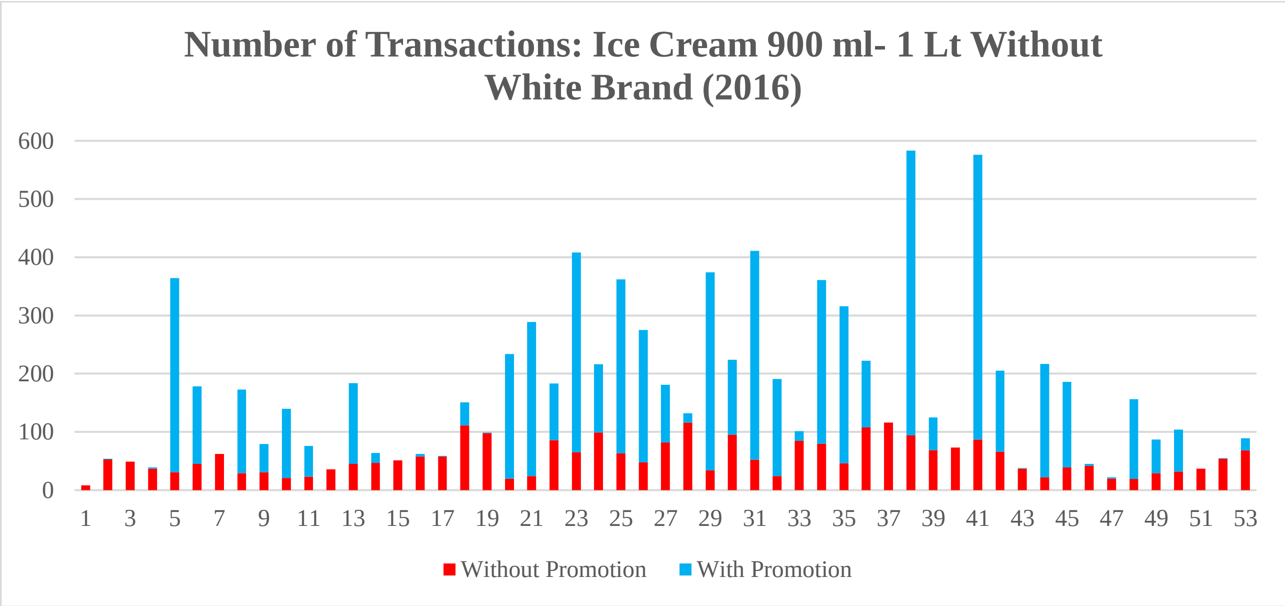


Figure 15: Number of Transactions: Ice Cream 900 ml- 1 Lt Without White Brand (2016)

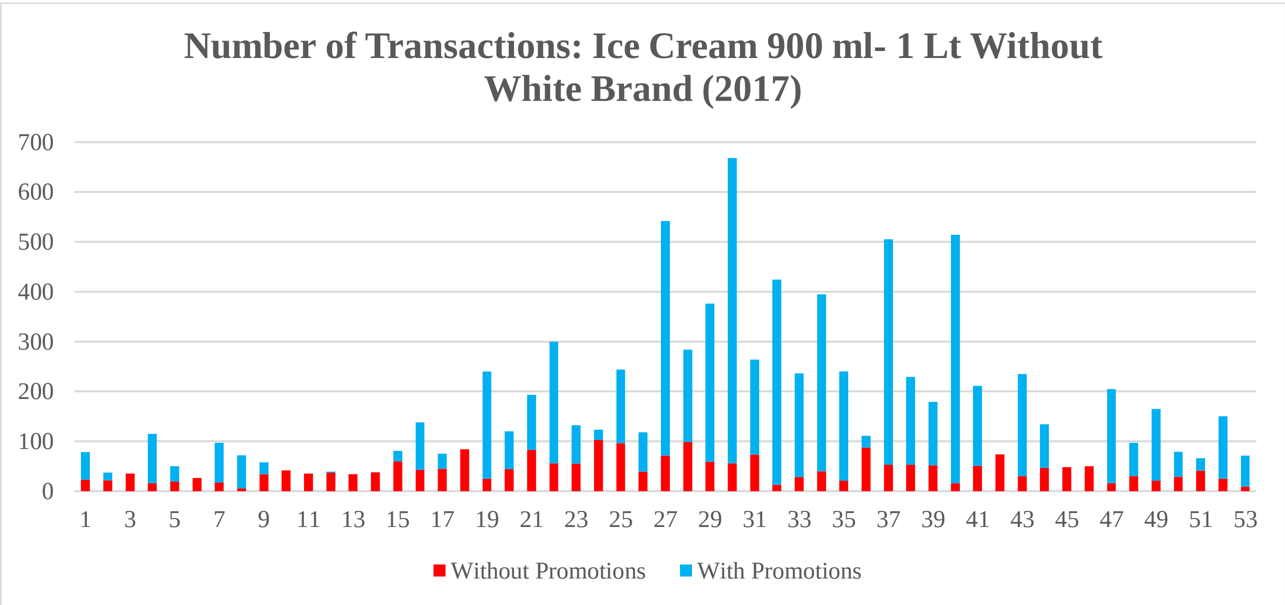


Figure 16: Number of Transactions: Ice Cream 900 ml- 1 Lt Without White Brand (2017)

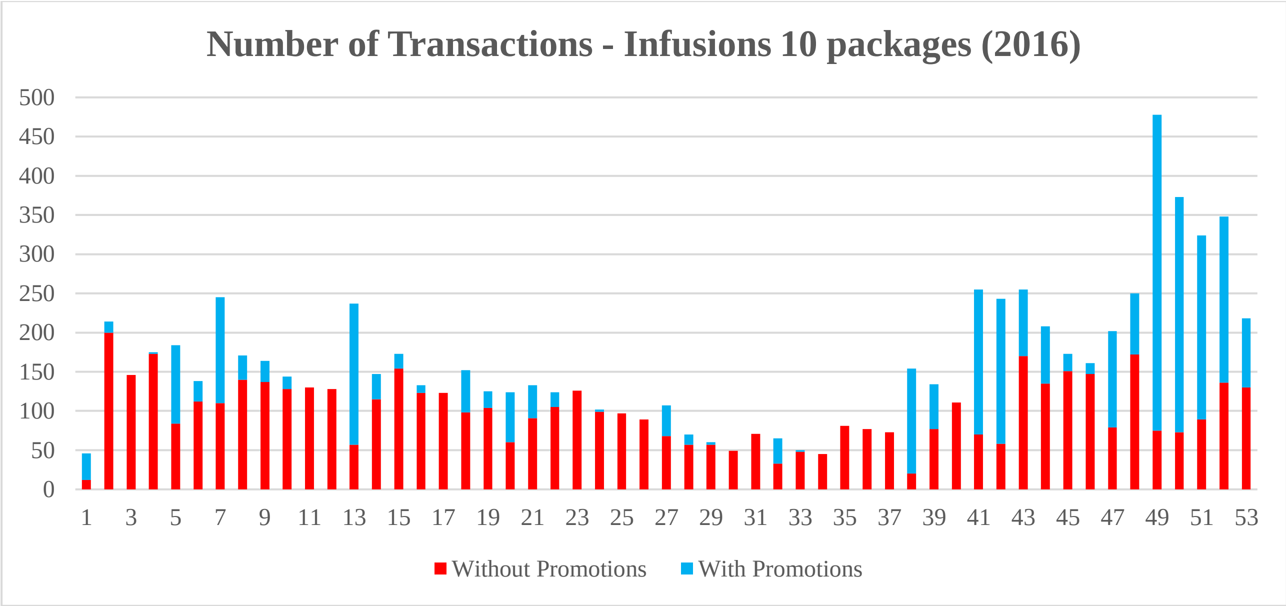


Figure 17: Number of Transactions - Infusions 10 packages (2016)

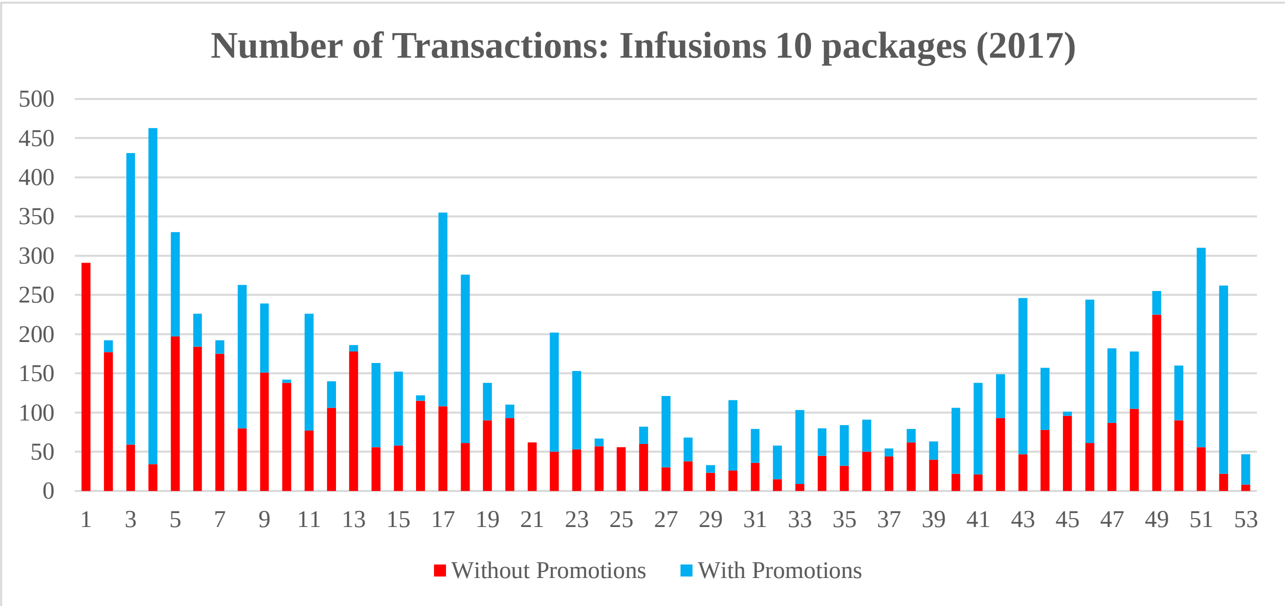


Figure 18: Number of Transactions: Infusions 10 packages (2017)

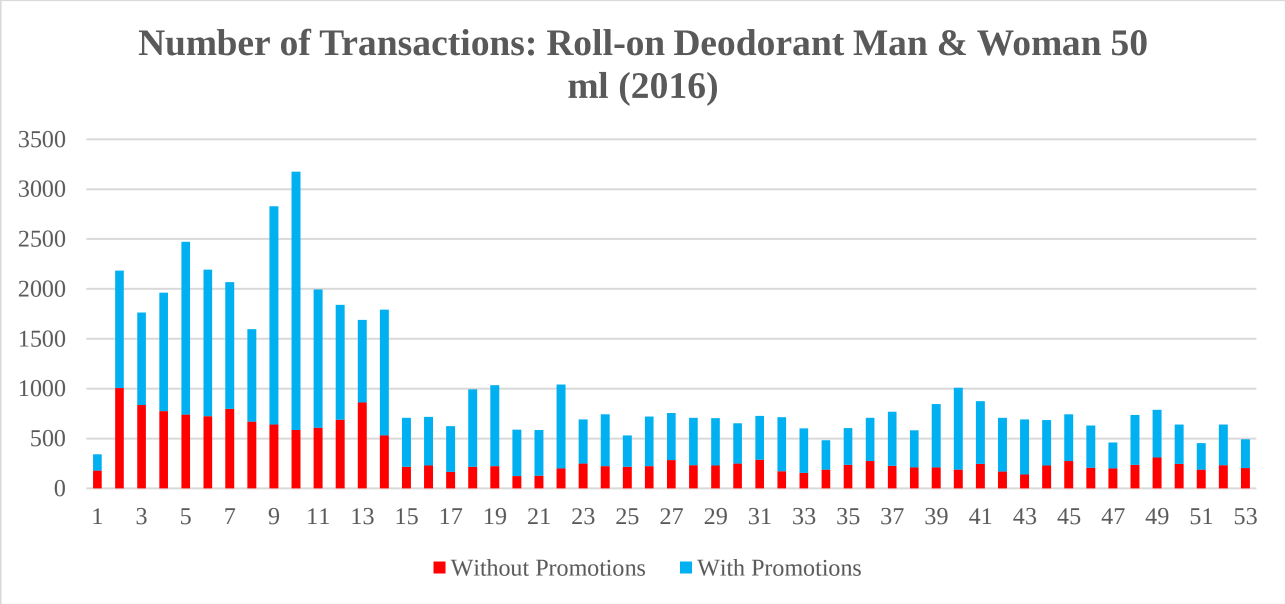


Figure 19: Number of Transactions: Roll-on Deodorant Man & Woman 50 ml (2016)

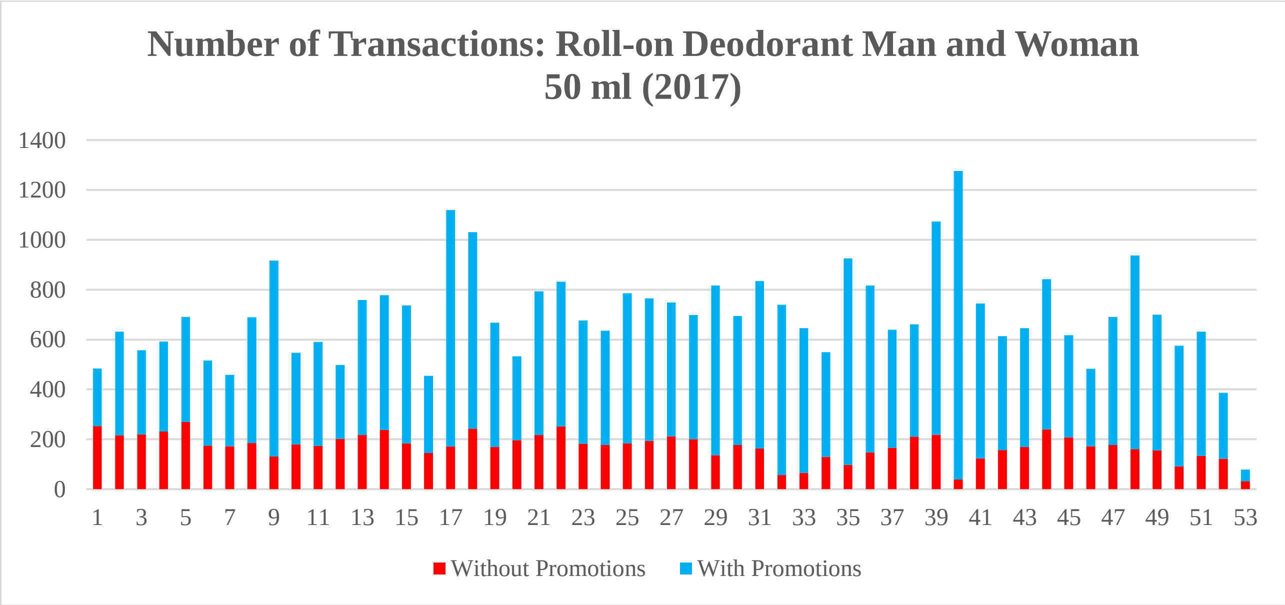


Figure 20: Number of Transactions: Roll-on Deodorant Man and Woman 50 ml (2017)

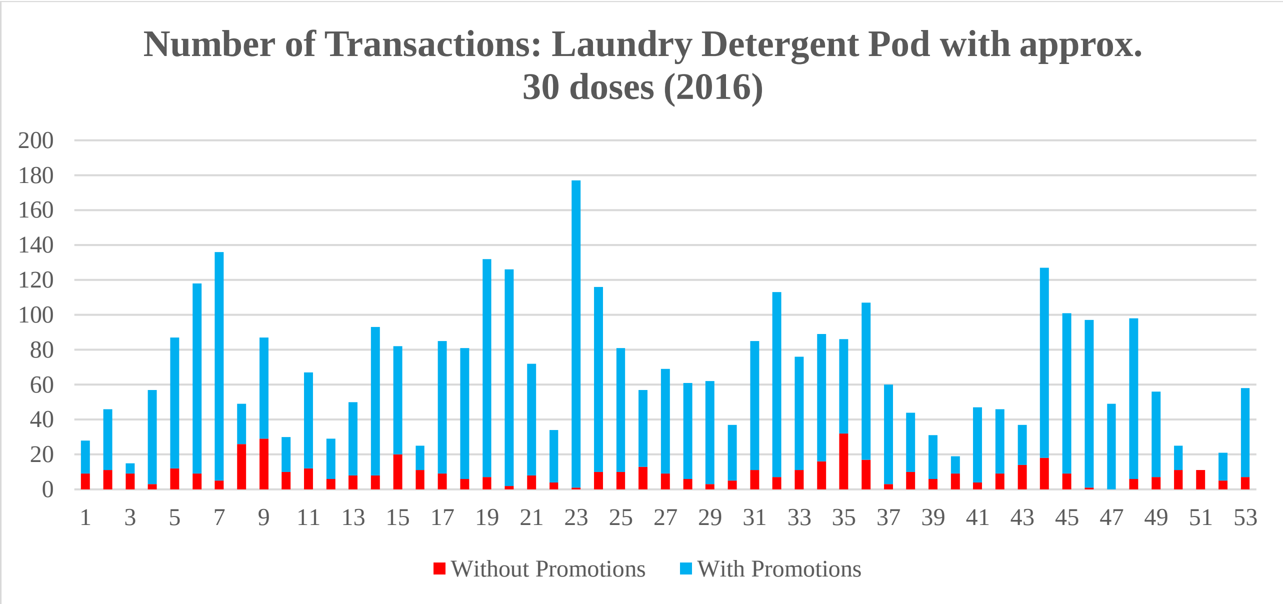


Figure 21: Number of Transactions: Laundry Detergent Pod with approx. 30 doses (2016)

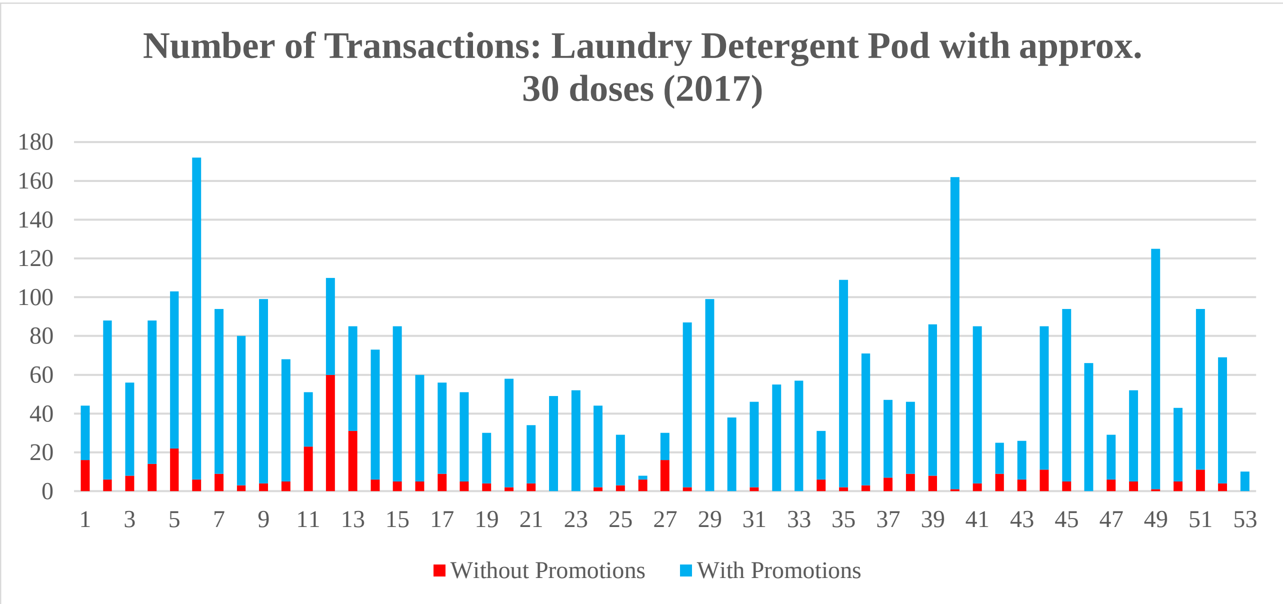


Figure 22: Number of Transactions: Laundry Detergent Pod with approx. 30 doses (2017)

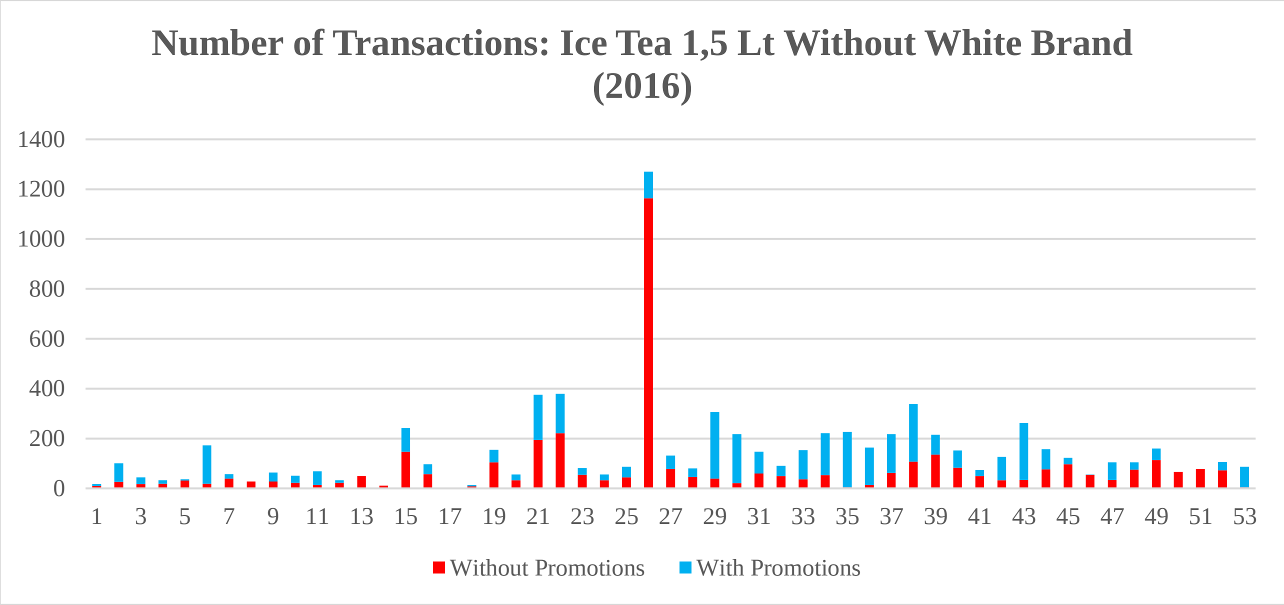


Figure 23: Number of Transactions: Ice Tea 1,5 Lt Without White Brand (2016)

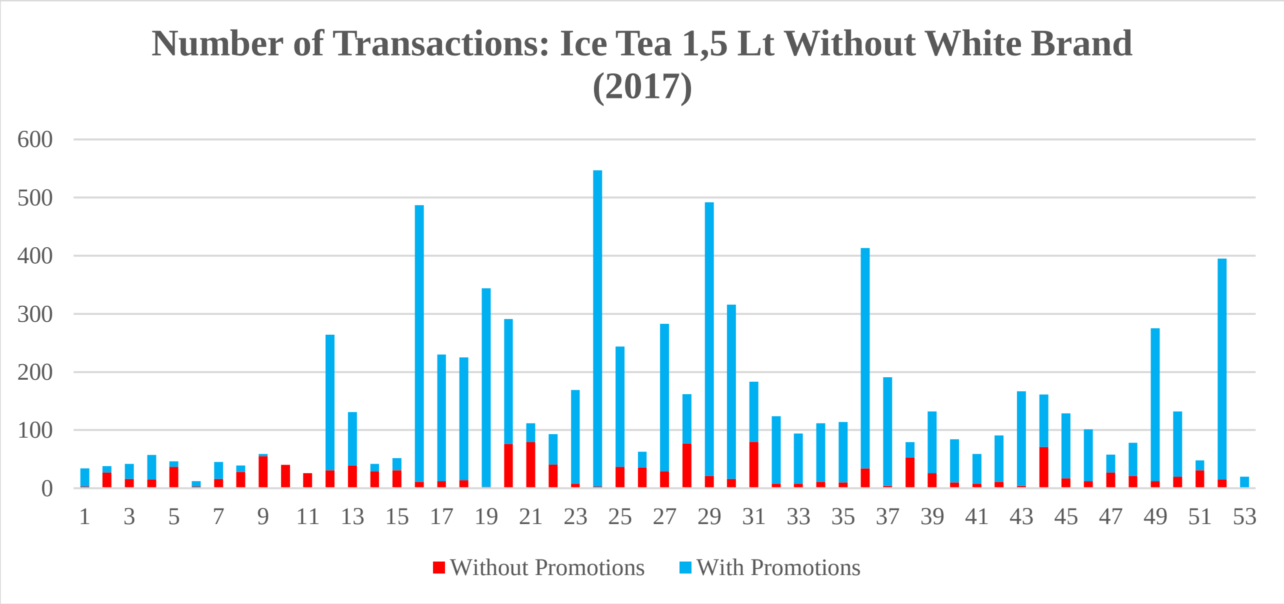


Figure 24: Number of Transactions: Ice Tea 1,5 Lt Without White Brand (2017)

- ABC COMPANY'S WHITE BRAND

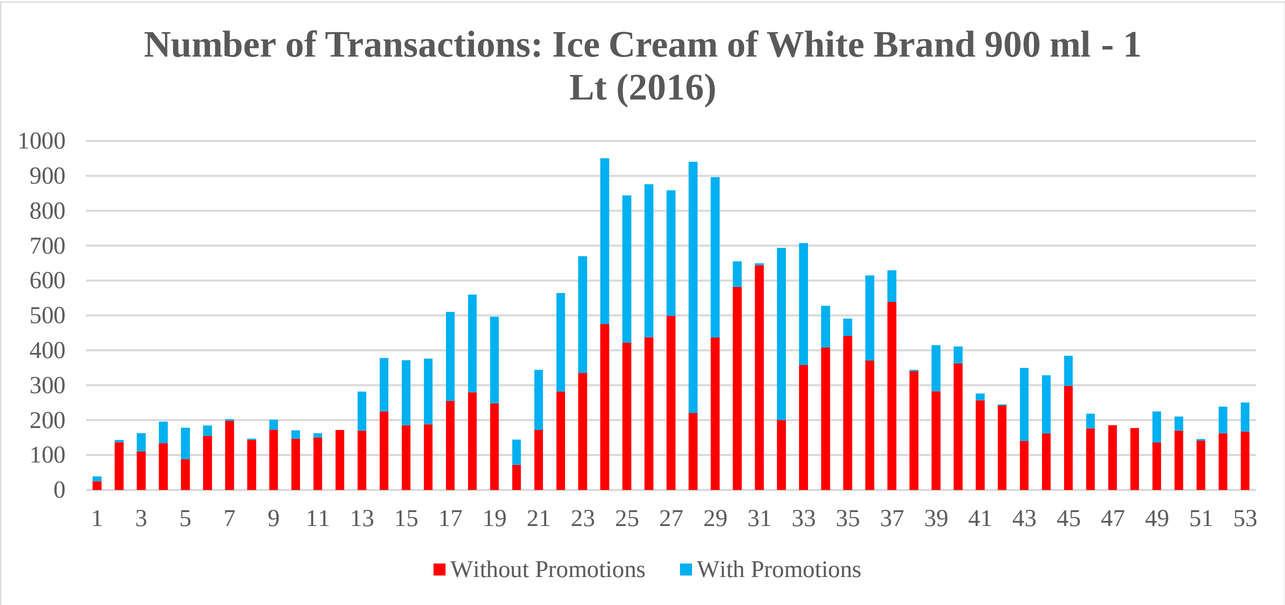


Figure 25: Number of Transactions: Ice Cream of White Brand 900 ml - 1 Lt (2016)

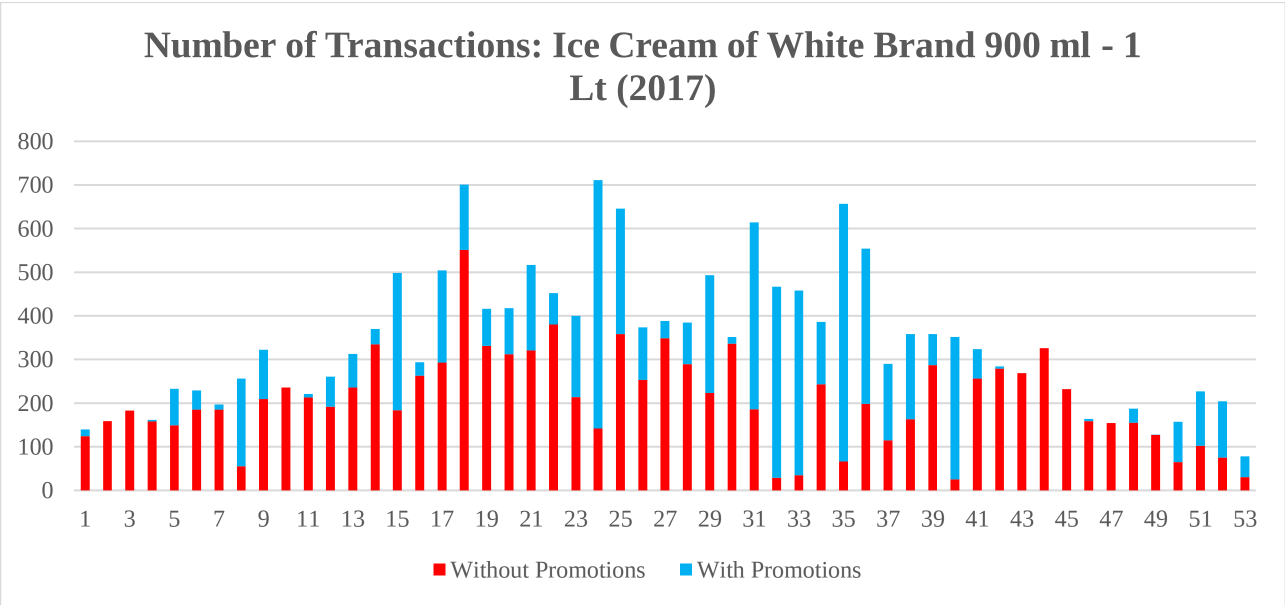


Figure 26: Number of Transactions: Ice Cream of White Brand 900 ml - 1 Lt (2017)

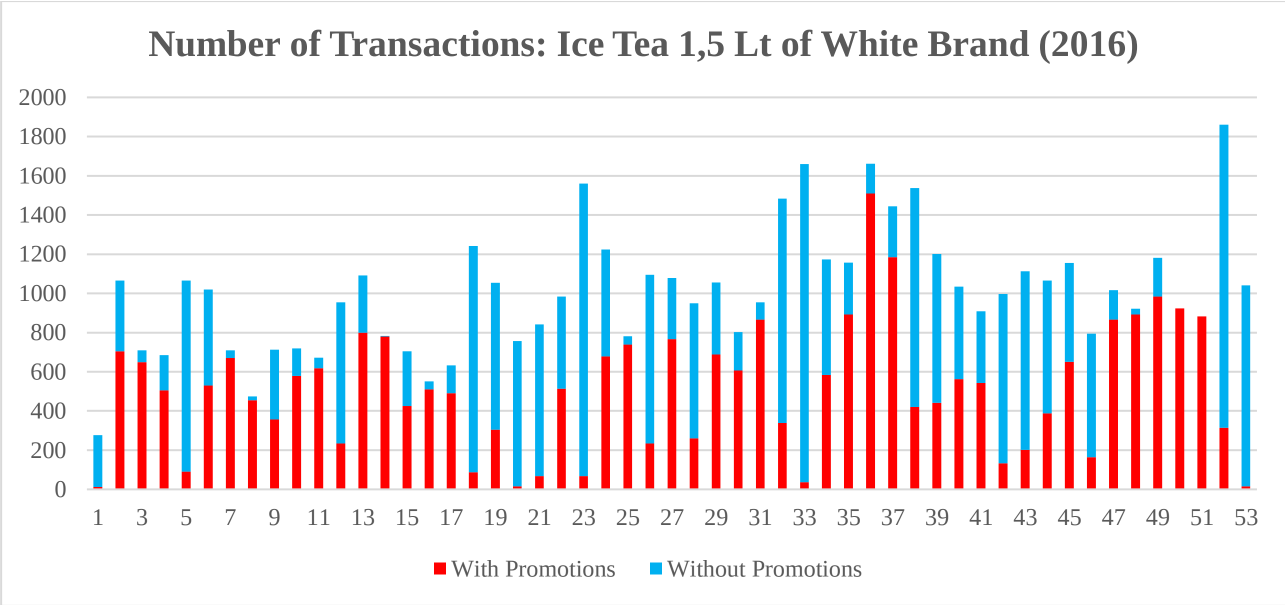


Figure 27: Number of Transactions: Ice Tea 1,5 Lt of White Brand (2016)

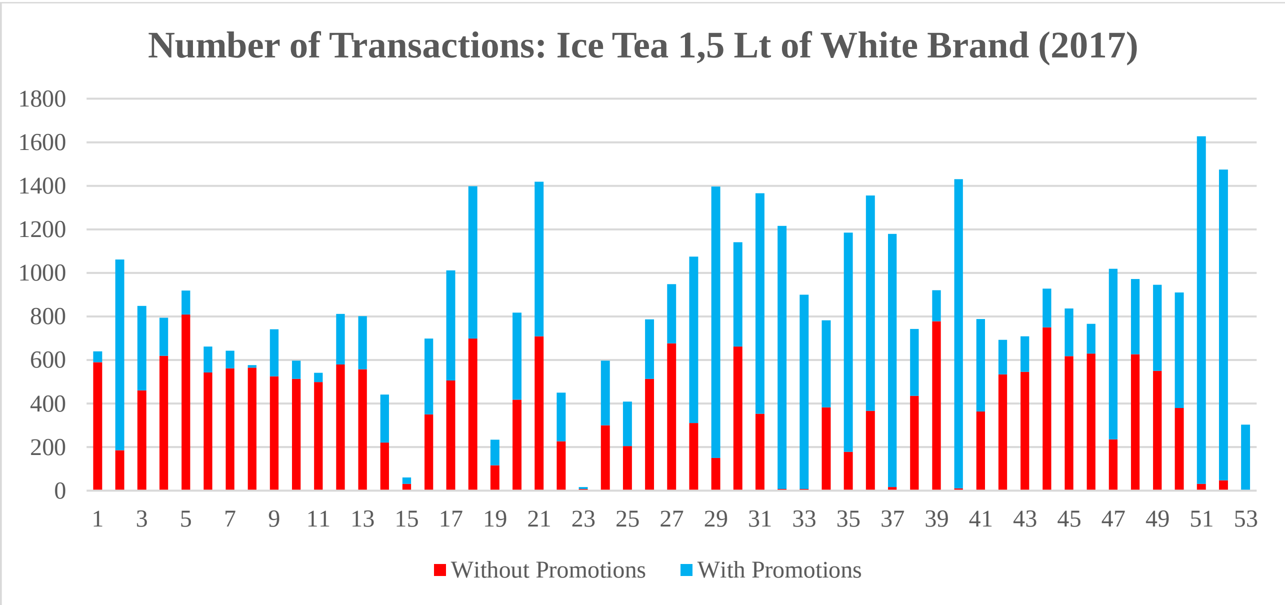


Figure 28: Number of Transactions: Ice Tea 1,5 Lt of White Brand (2017)

APPENDIX 5 – CANNIBALISATION EFFECT

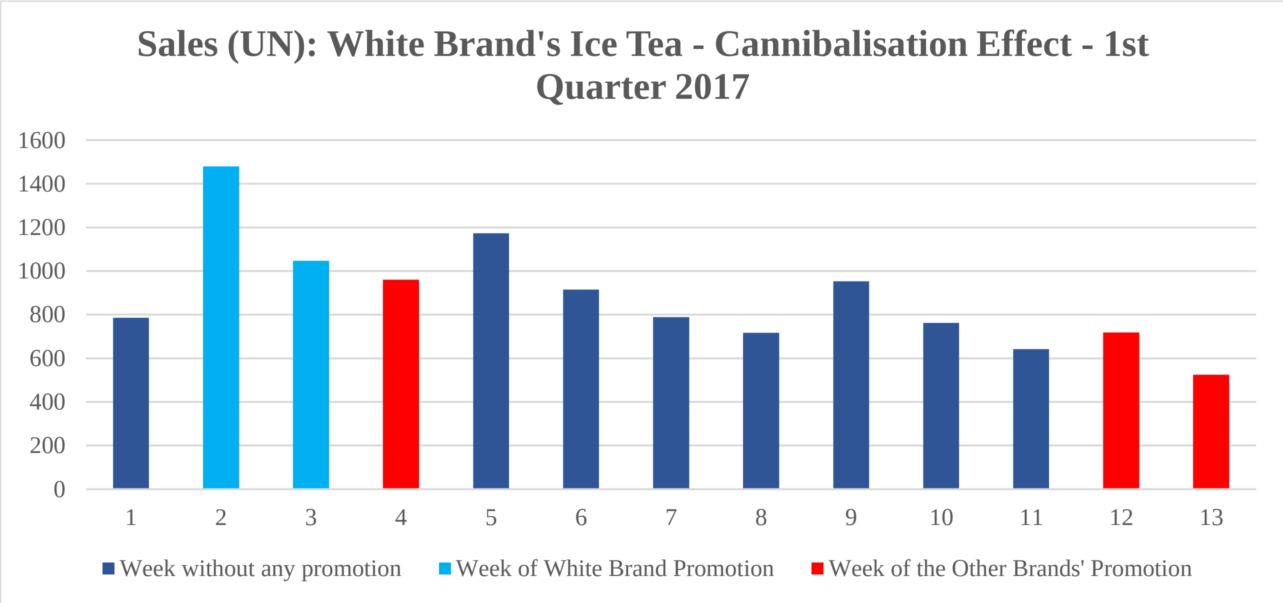


Figure 1: Sales (UN): White Brand's Ice Tea - Cannibalisation Effect - 1st Quarter 2017

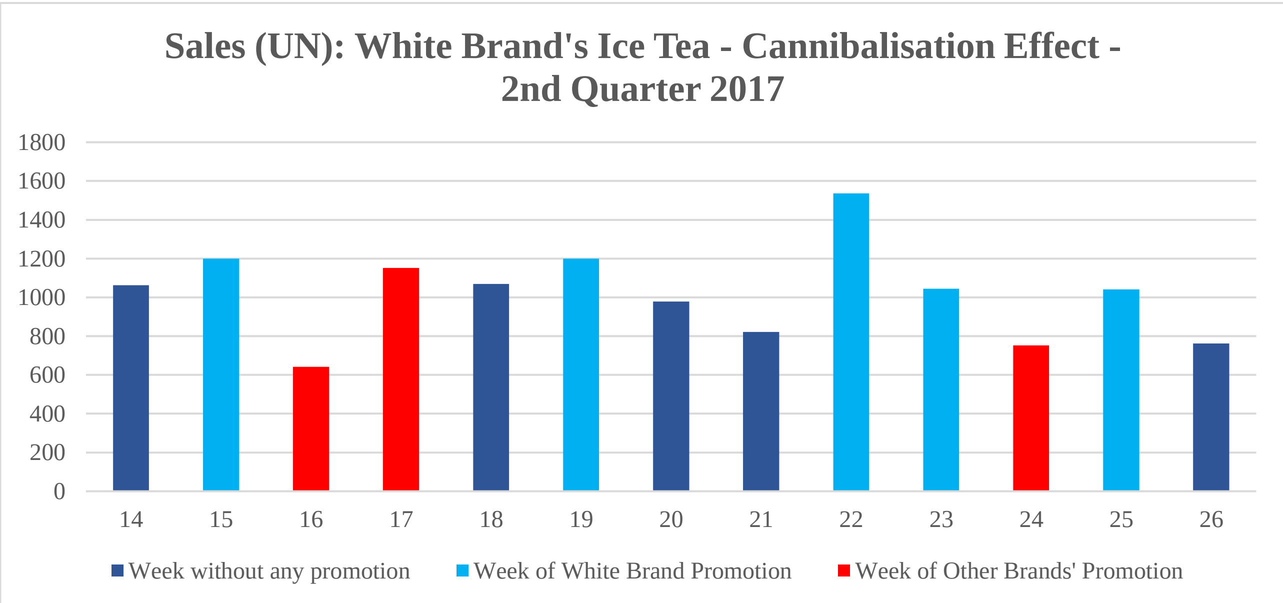


Figure 2: Sales (UN): White Brand's Ice Tea - Cannibalisation Effect - 2nd Quarter 2017

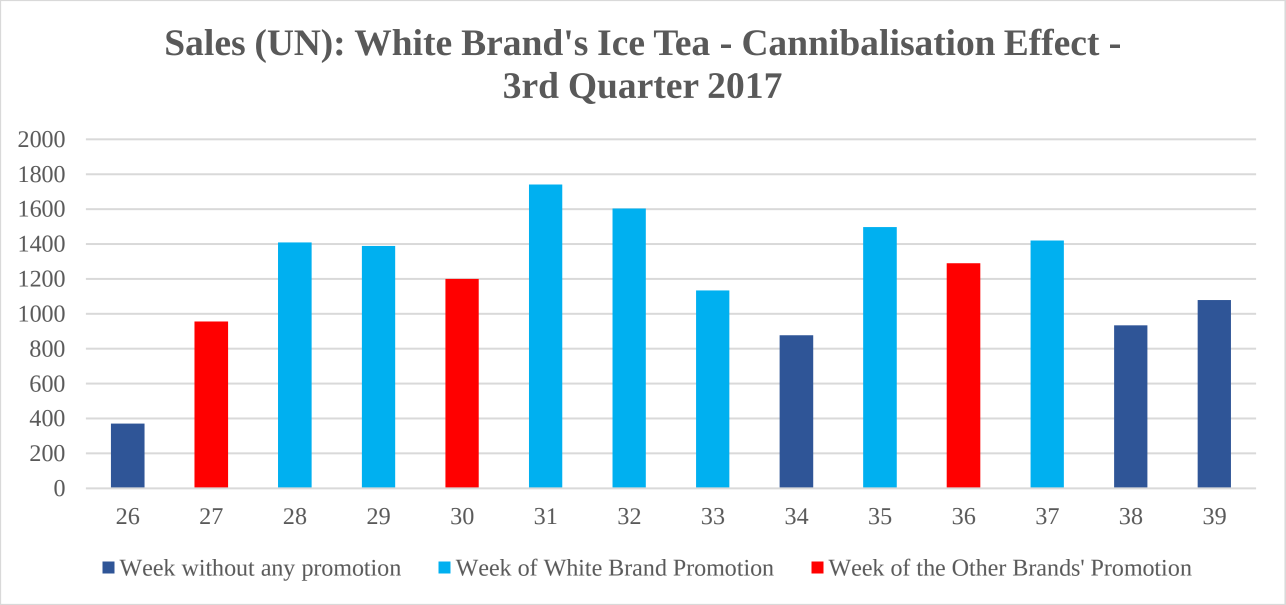


Figure 3: Sales (UN): White Brand's Ice Tea - Cannibalisation Effect - 3rd Quarter 2017

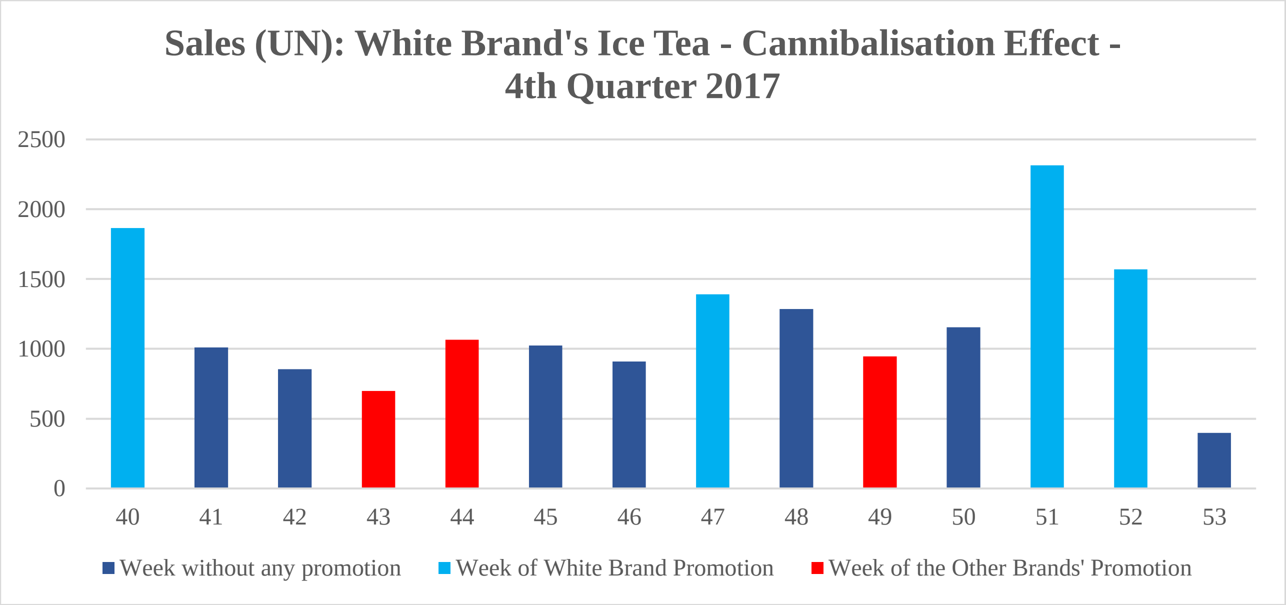


Figure 4: Sales (UN): White Brand's Ice Tea - Cannibalisation Effect - 4th Quarter 2017

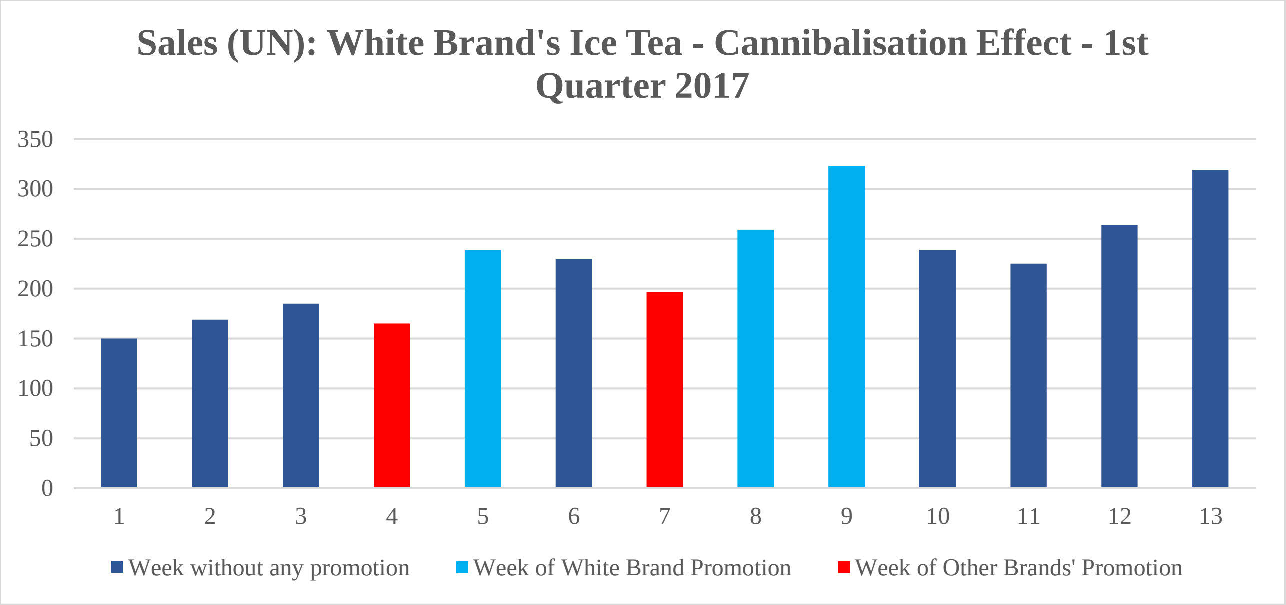


Figure 5: Sales (UN): White Brand's Ice Tea - Cannibalisation Effect - 1st Quarter 2017

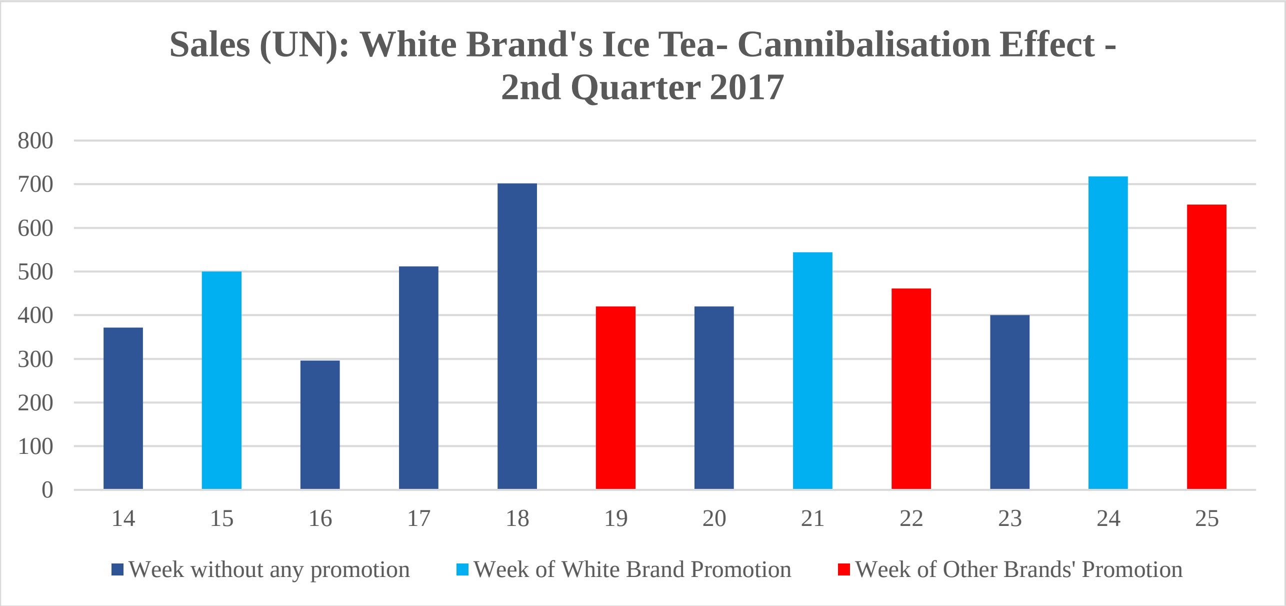


Figure 6: Sales (UN): White Brand's Ice Tea- Cannibalisation Effect - 2nd Quarter 2017

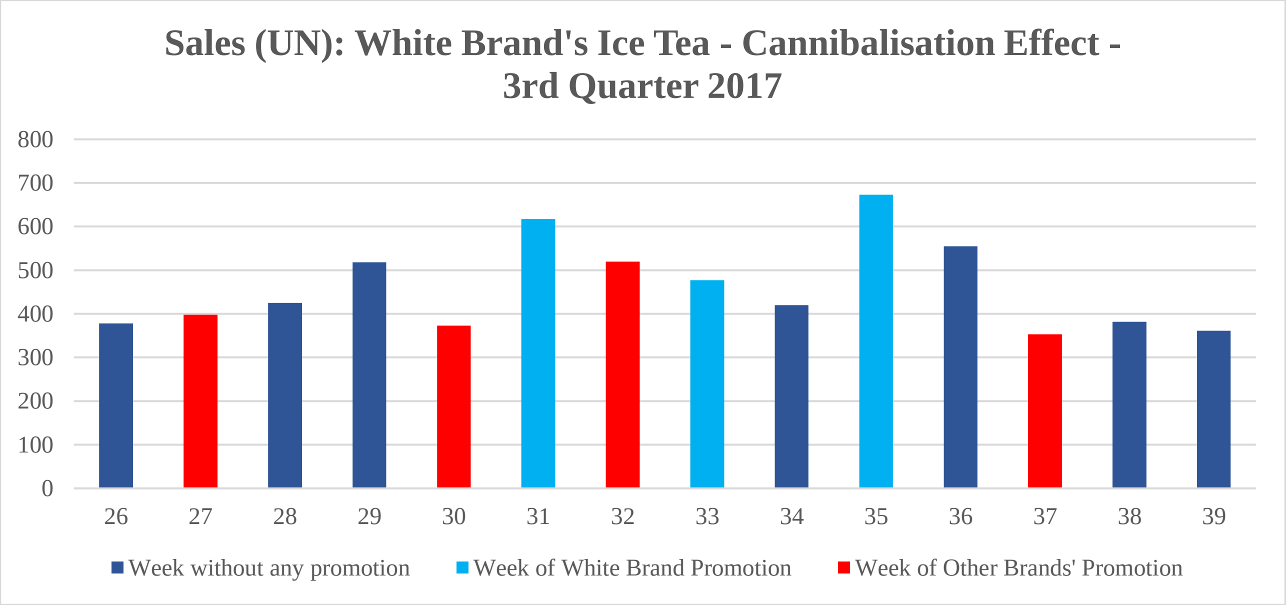


Figure 7: Sales (UN): White Brand's Ice Tea - Cannibalisation Effect - 3rd Quarter 2017

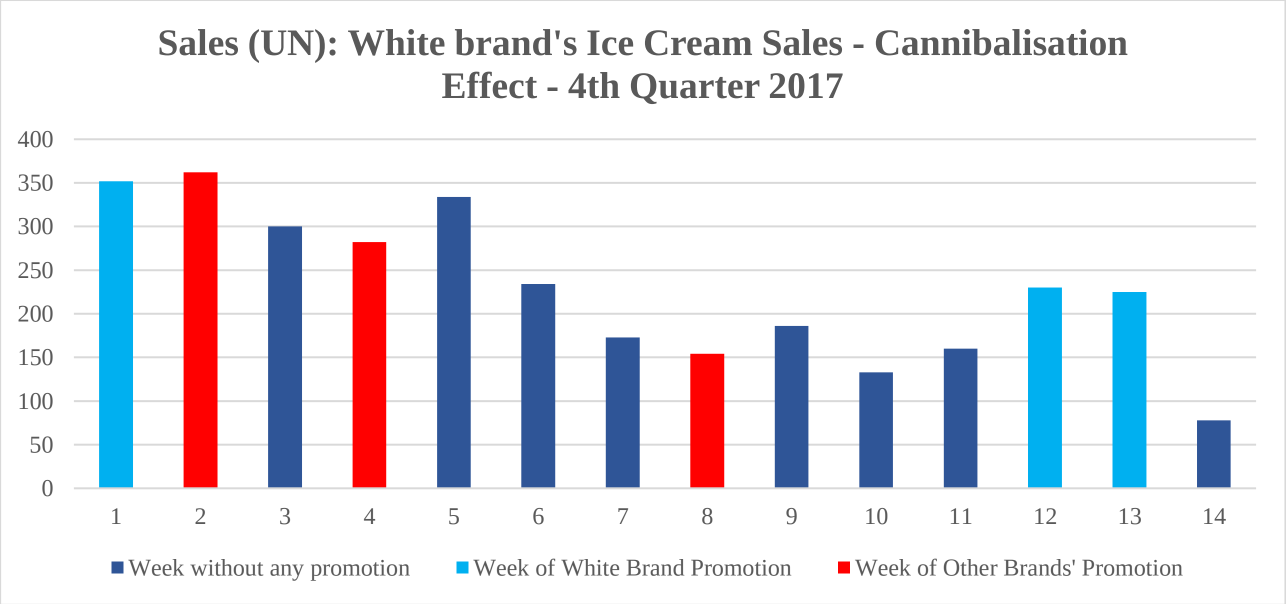


Figure 8: Sales (UN): White brand's Ice Cream Sales - Cannibalisation Effect - 4th Quarter 2017

APPENDIX 6 – EFFECT OF PROMOTIONS

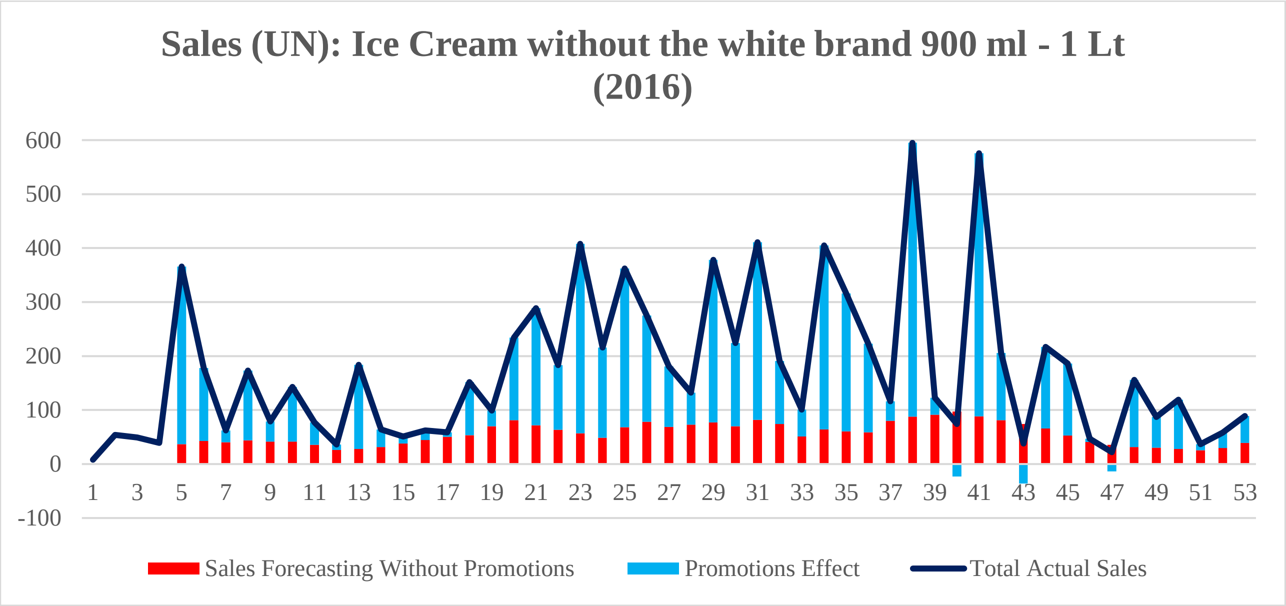


Figure 1: Sales (UN): Ice Cream without the white brand 900 ml – 1 Lt (2016)

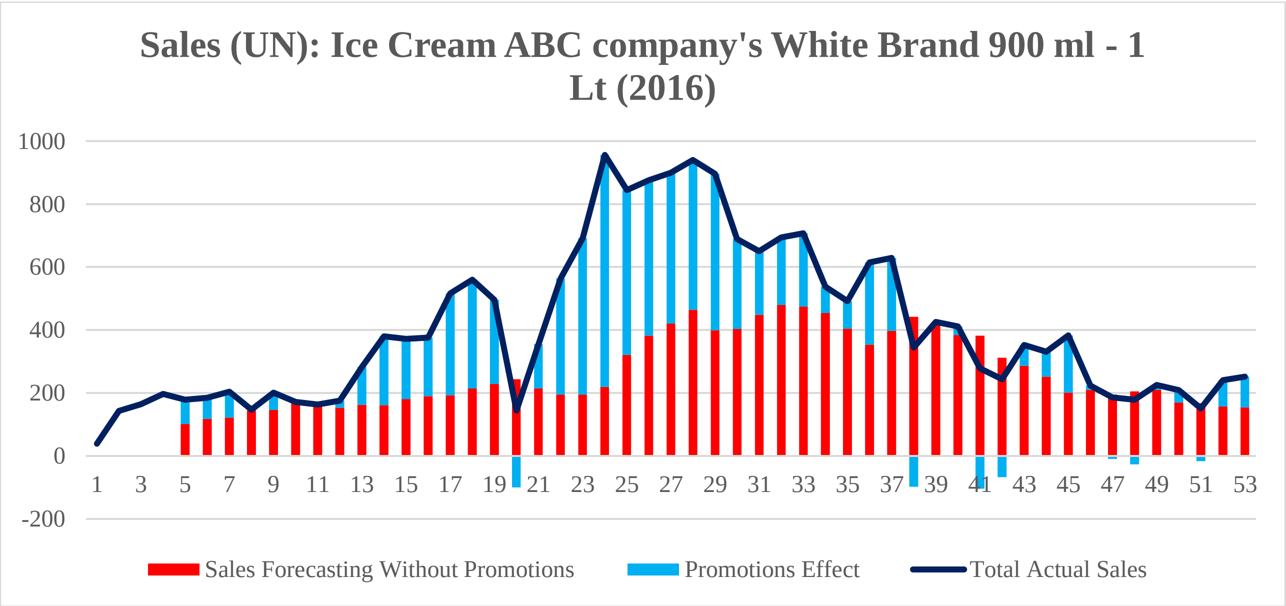


Figure 2: Sales (UN): Ice Cream ABC company's White Brand 900 ml – 1 Lt (2016)

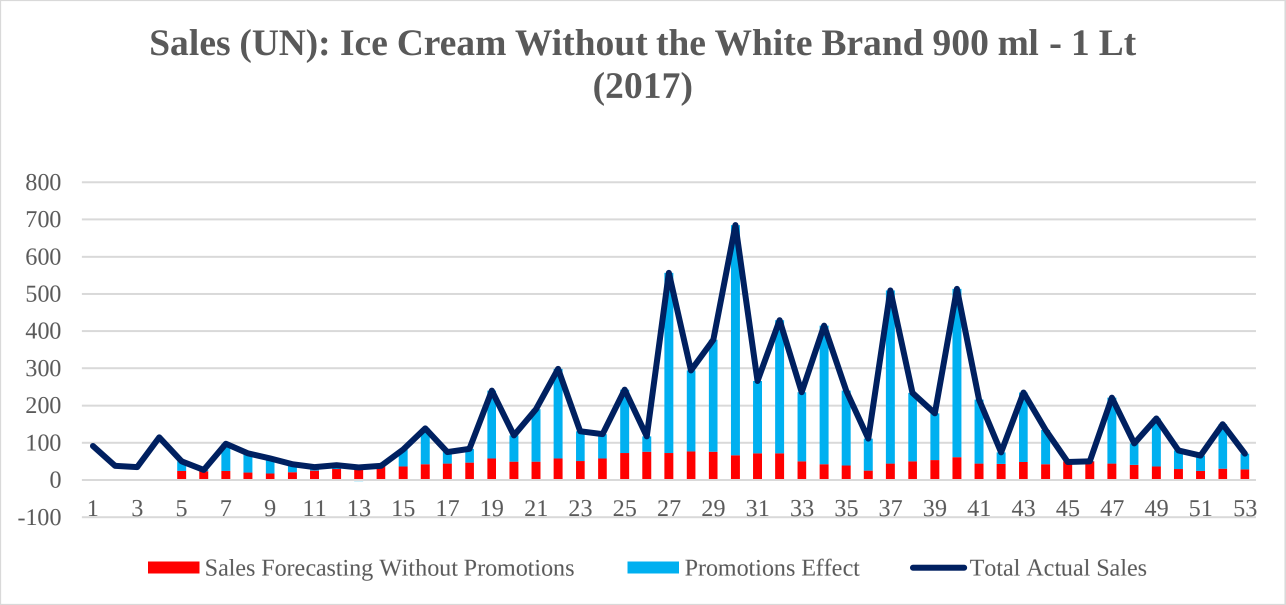


Figure 3: Sales (UN): Ice Cream Without the White Brand 900 ml - 1 Lt (2017)

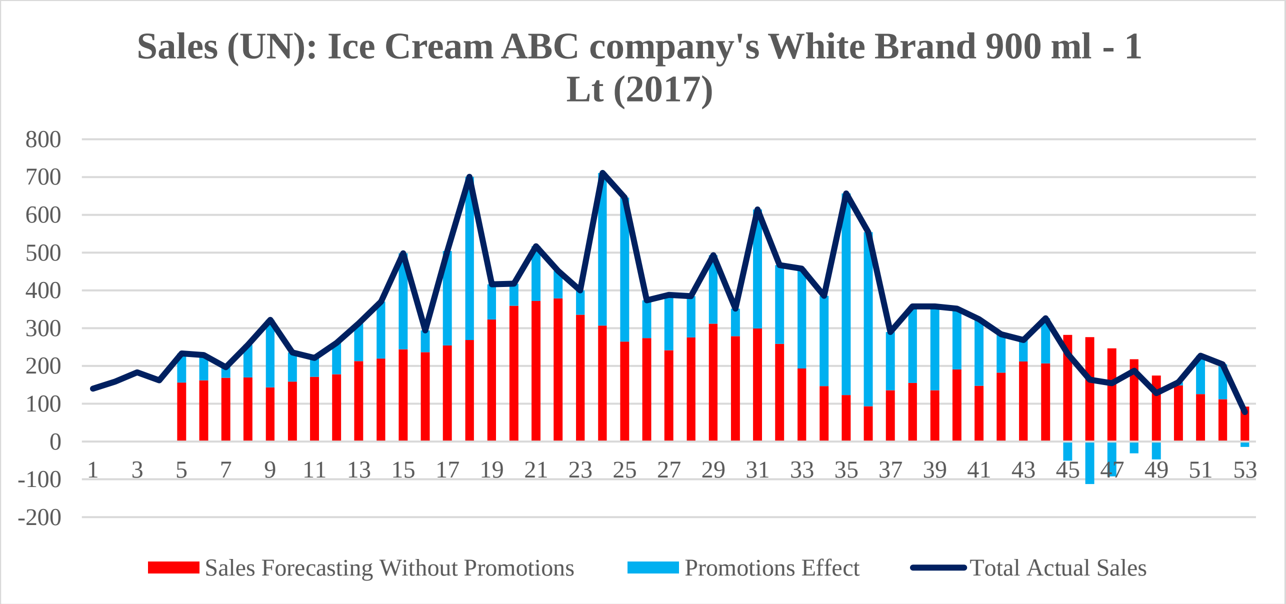


Figure 4: Sales (UN): Ice Cream ABC company's White Brand 900 ml - 1 Lt (2017)

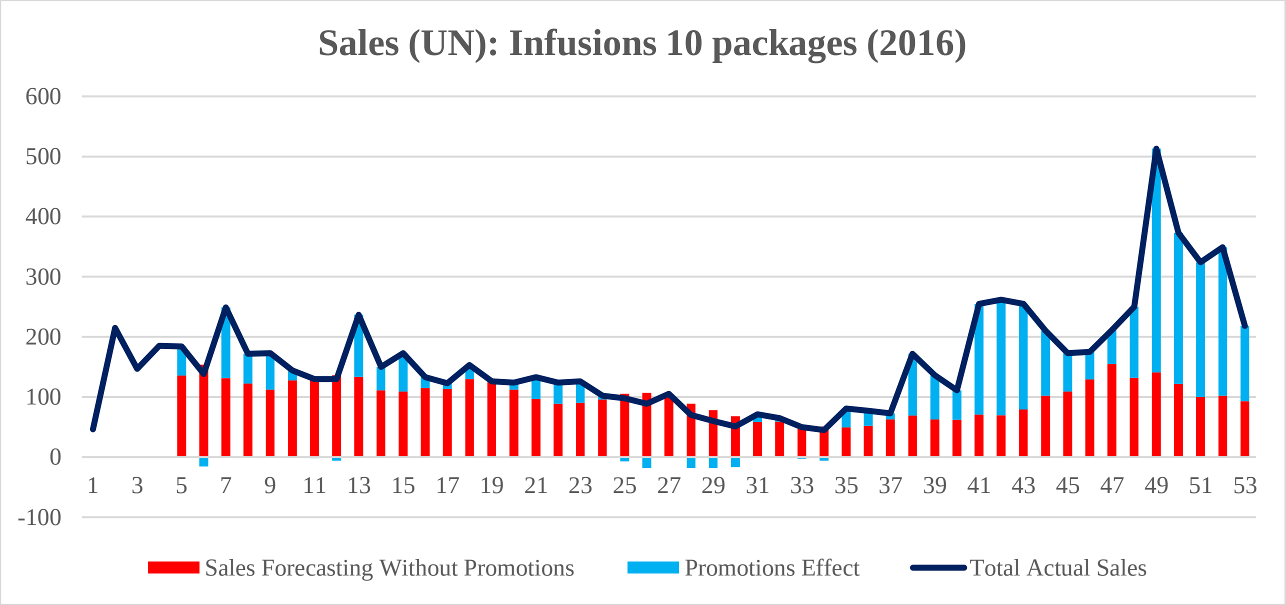


Figure 5: Sales (UN): Infusions 10 packages (2016)

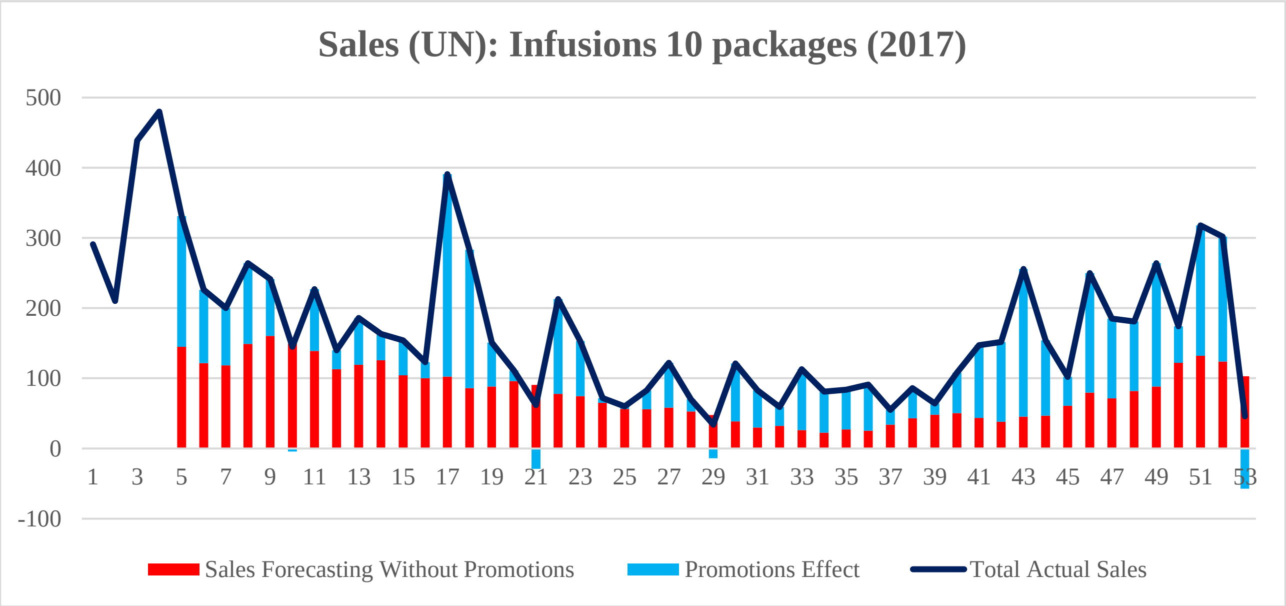


Figure 6: Sales (UN): Infusions 10 packages (2017)

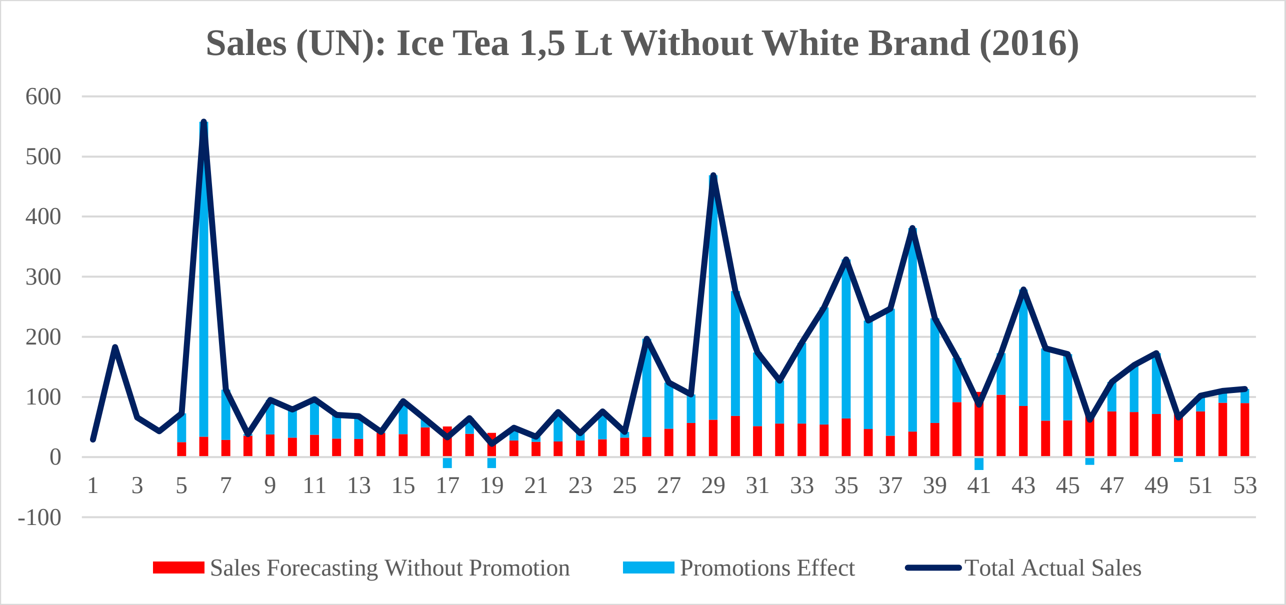


Figure 7: Sales (UN): Ice Tea 1,5 Lt Without White Brand (2016)

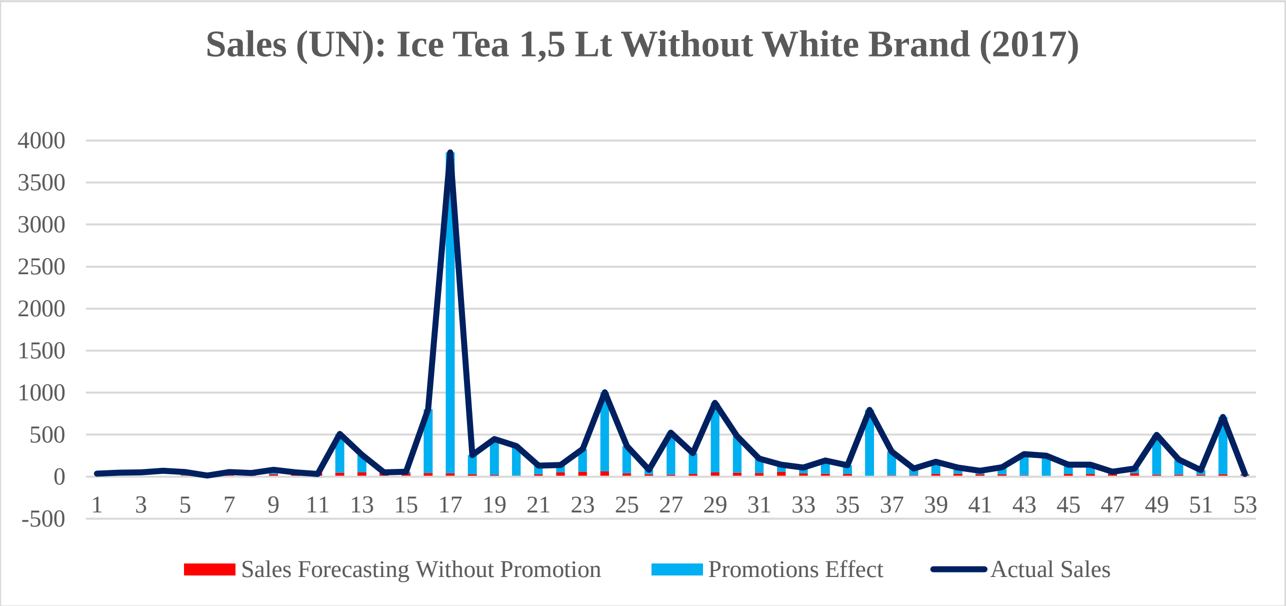


Figure 8: Sales (UN): Ice Tea 1,5 Lt Without White Brand (2017)

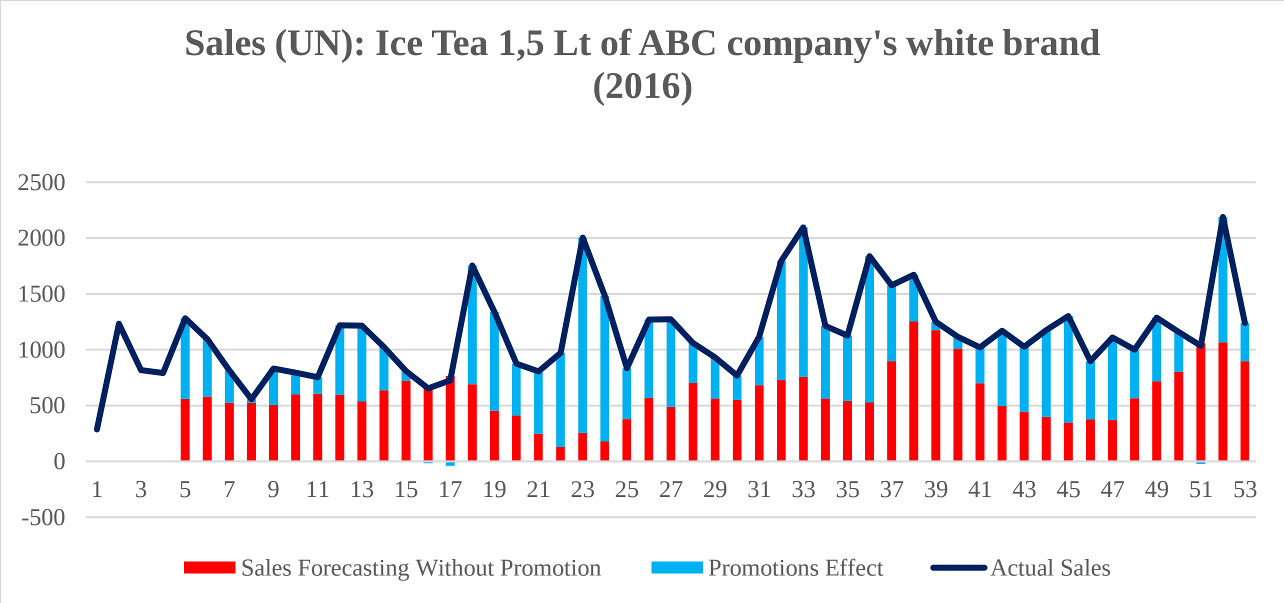


Figure 9: Sales (UN): Ice Tea 1,5 Lt of ABC company's white brand (2016)

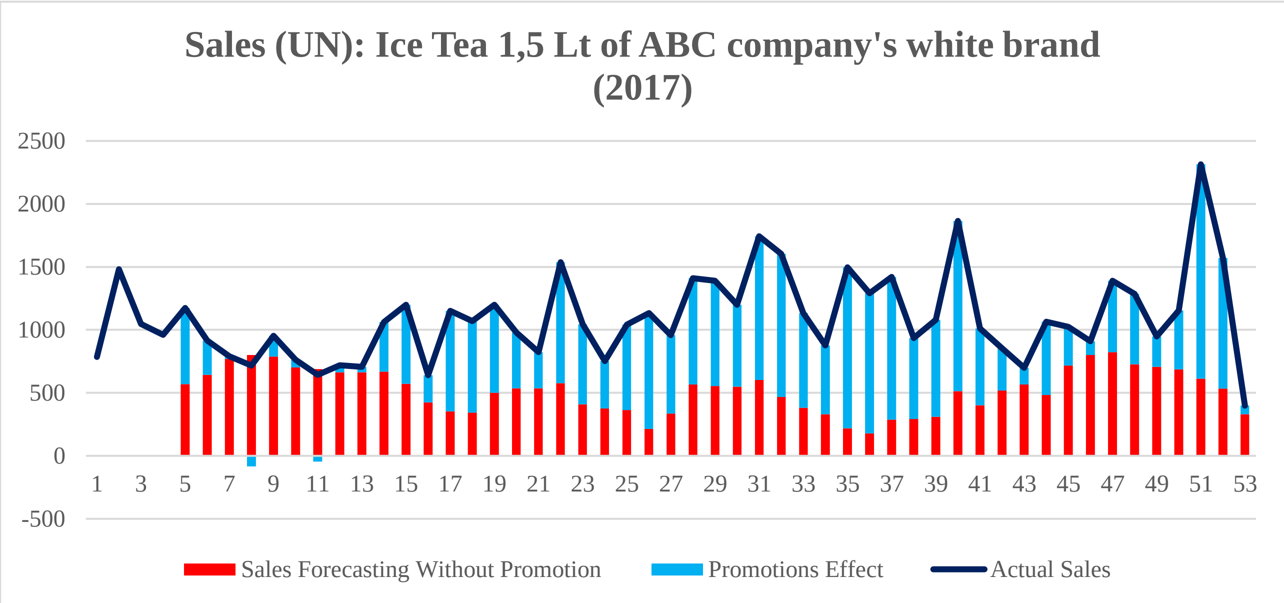


Figure 10: Sales (UN): Ice Tea 1,5 Lt of ABC company's white brand (2017)

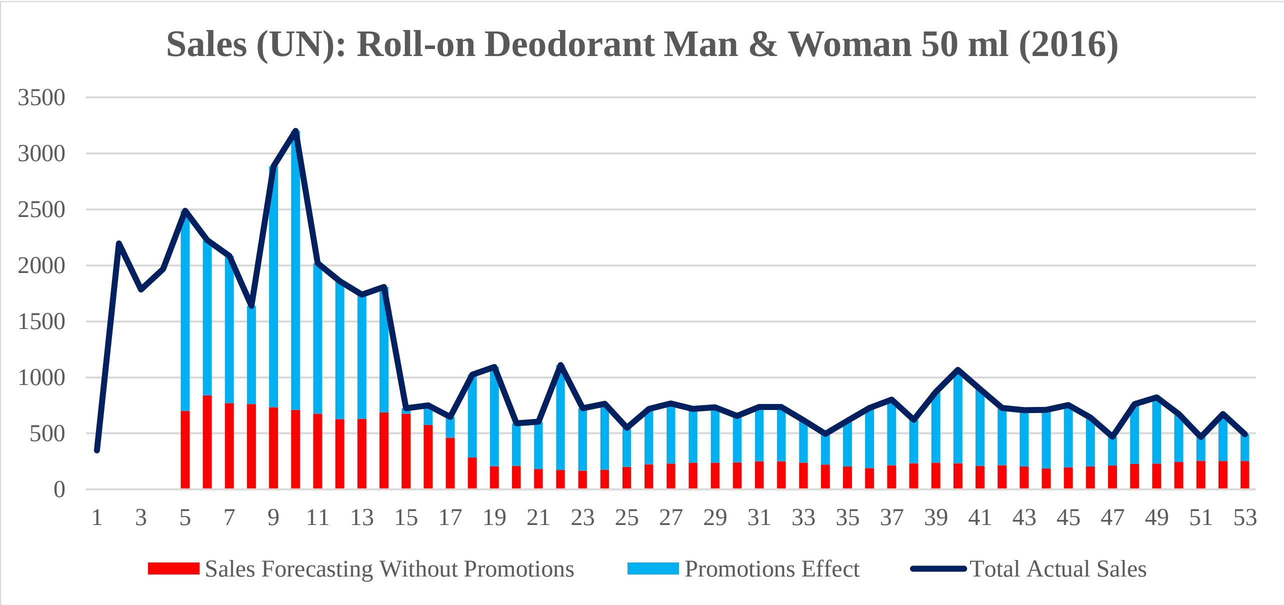


Figure 11: Sales (UN): Roll-on Deodorant Man & Woman 50 ml (2016)

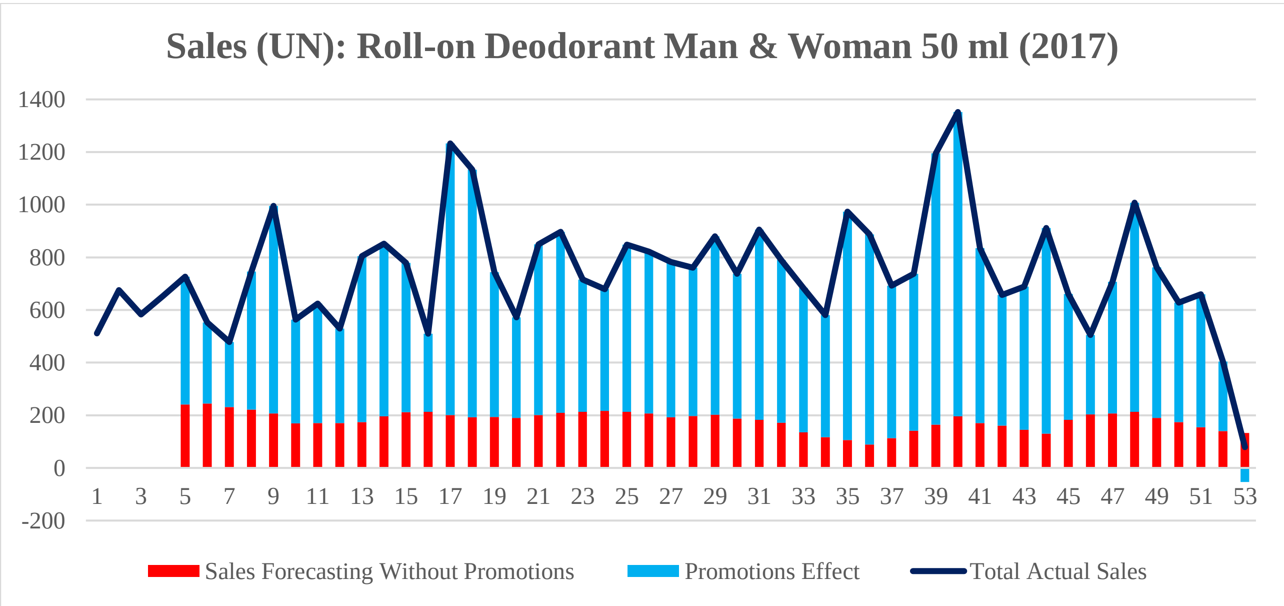


Figure 12: Sales (UN): Roll-on Deodorant Man & Woman 50 ml (2017)

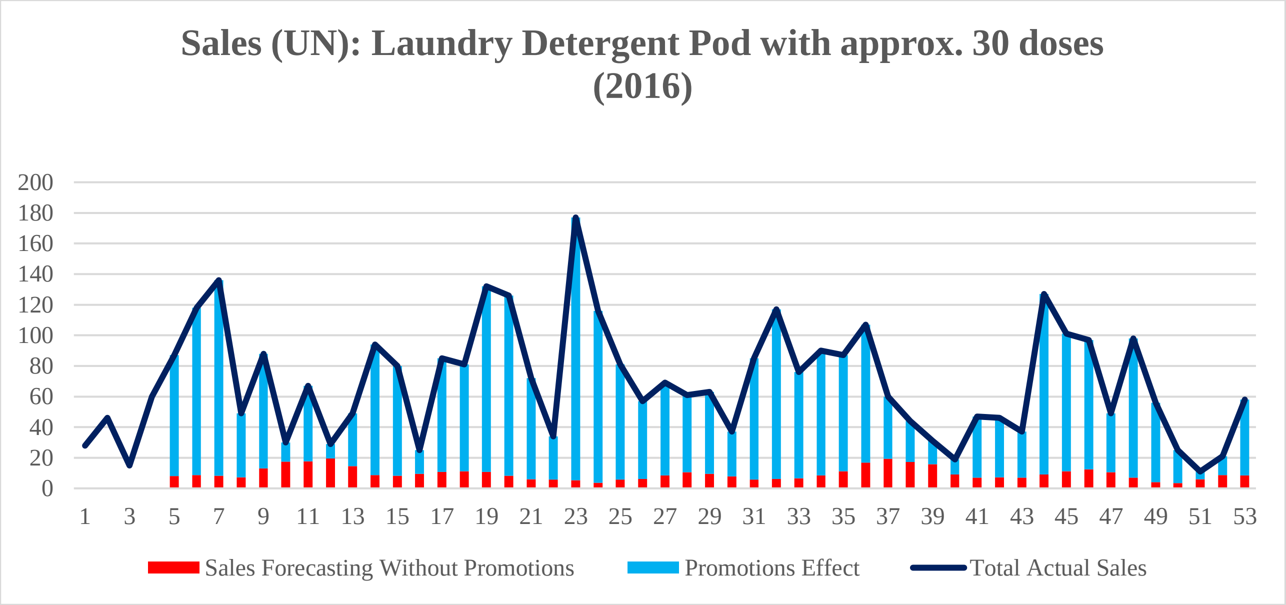


Figure 13: Sales (UN): Laundry Detergent Pod with approx. 30 doses (2016)

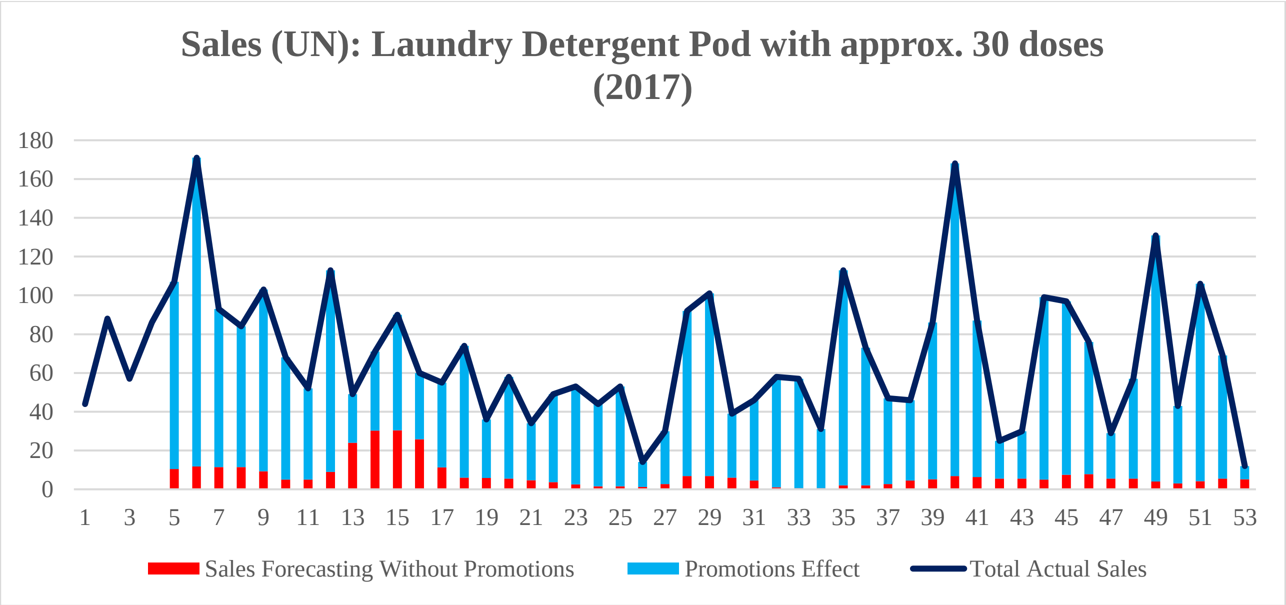


Figure 14: Sales (UN): Laundry Detergent Pod with approx. 30 doses (2017)

APPENDIX 7 – BOX-JENKINS APPROACH - ICE CREAM

Table 1: Augmented Dickey-Fuller Test for Ice Cream's Sales Without Promotions – 2016 and 2017

Null Hypothesis: SALES has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.259872	0.1870
Test critical values:	1% level	-3.495021	
	5% level	-2.889753	
	10% level	-2.581890	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SALES)
Method: Least Squares
Sample (adjusted): 1/17/2016 12/31/2017
Included observations: 103 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SALES(-1)	-0.199714	0.088374	-2.259872	0.0260
D(SALES(-1))	-0.319447	0.106729	-2.993054	0.0035
D(SALES(-2))	-0.296325	0.095423	-3.105372	0.0025
C	93.25689	44.77044	2.083001	0.0398

R-squared	0.266618	Mean dependent var	-2.582524
Adjusted R-squared	0.244394	S.D. dependent var	169.0733
S.E. of regression	146.9680	Akaike info criterion	12.85637
Sum squared resid	2138359.	Schwarz criterion	12.95869
Log likelihood	-658.1029	Hannan-Quinn criter.	12.89781
F-statistic	11.99702	Durbin-Watson stat	2.013430
Prob(F-statistic)	0.000001		

Table 2: Augmented Dickey-Fuller Test for the 1st Difference of Ice Cream's Sales Without Promotions – 2016 and 2017

Null Hypothesis: D(SALES) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.06217	0.0000
Test critical values:	1% level	-3.495021	
	5% level	-2.889753	
	10% level	-2.581890	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SALES,2)
Method: Least Squares
Sample (adjusted): 1/17/2016 12/31/2017
Included observations: 103 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(SALES(-1))	-1.813018	0.150306	-12.06217	0.0000
D(SALES(-1),2)	0.368148	0.091804	4.010149	0.0001
C	-2.478905	14.77673	-0.167757	0.8671

R-squared	0.707951	Mean dependent var	-1.184466
Adjusted R-squared	0.702110	S.D. dependent var	274.7480
S.E. of regression	149.9556	Akaike info criterion	12.88725
Sum squared resid	2248669.	Schwarz criterion	12.96399
Log likelihood	-660.6933	Hannan-Quinn criter.	12.91833
F-statistic	121.2039	Durbin-Watson stat	2.069422
Prob(F-statistic)	0.000000		

Table 3: Equation - ARIMA(2,1,2)

Dependent Variable: D(LOG(SALES))
Method: Least Squares
Sample (adjusted): 1/17/2016 12/31/2017
Included observations: 103 after adjustments
Convergence achieved after 10 iterations
MA Backcast: 1/03/2016 1/10/2016

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.006869	0.012956	-0.530167	0.5972
AR(1)	-0.477442	0.102881	-4.640736	0.0000
AR(2)	-0.030896	0.142523	-0.216776	0.8288
MA(2)	-0.503344	0.147477	-3.413027	0.0009

R-squared	0.249694	Mean dependent var	-0.014703
Adjusted R-squared	0.226958	S.D. dependent var	0.441908
S.E. of regression	0.388538	Akaike info criterion	0.985210
Sum squared resid	14.94522	Schwarz criterion	1.087529
Log likelihood	-46.73830	Hannan-Quinn criter.	1.026653
F-statistic	10.98206	Durbin-Watson stat	1.931277
Prob(F-statistic)	0.000003		

Inverted AR Roots	-.08	-.40
Inverted MA Roots	.71	-.71

Table 4: Equation - ARIMA(2,1,2), restricted MA(1)=0

Dependent Variable: D(LOG(SALES))
Method: Least Squares
Sample (adjusted): 1/17/2016 12/31/2017
Included observations: 103 after adjustments
Convergence achieved after 13 iterations
MA Backcast: 1/03/2016 1/10/2016

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.007868	0.014861	-0.529417	0.5977
AR(1)	-0.763526	0.155603	-4.906884	0.0000
AR(2)	0.005723	0.150107	0.038127	0.9697
MA(1)	0.321301	0.126094	2.548101	0.0124
MA(2)	-0.641813	0.126417	-5.076943	0.0000

R-squared	0.280335	Mean dependent var	-0.014703
Adjusted R-squared	0.250960	S.D. dependent var	0.441908
S.E. of regression	0.382459	Akaike info criterion	0.962933
Sum squared resid	14.33490	Schwarz criterion	1.090832
Log likelihood	-44.59104	Hannan-Quinn criter.	1.014736
F-statistic	9.543596	Durbin-Watson stat	1.948424
Prob(F-statistic)	0.000001		

Inverted AR Roots	.01	-.77
Inverted MA Roots	.66	-.98

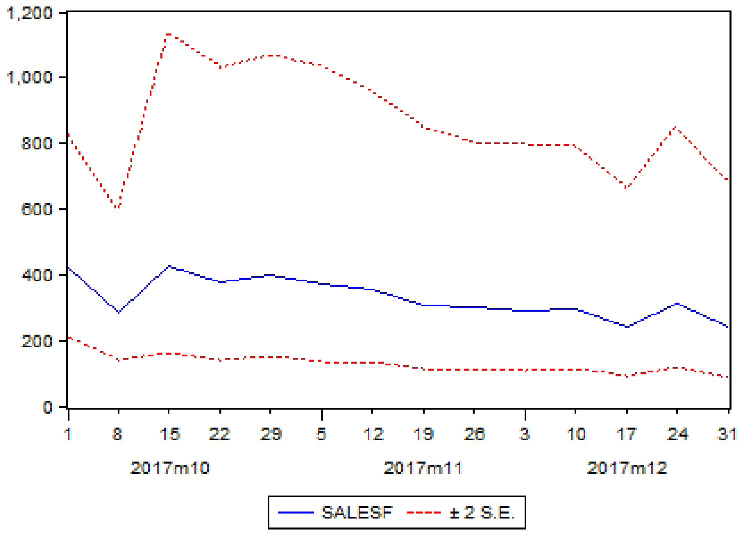
Table 5: ARIMA(2,1,2), restricted MA(1)=0, augmented by quarterly trend

Dependent Variable: D(LOG(SALES))
Method: Least Squares
Sample (adjusted): 1/17/2016 12/31/2017
Included observations: 103 after adjustments
Convergence achieved after 12 iterations
MA Backcast: 1/03/2016 1/10/2016

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.032763	0.050940	-0.643171	0.5217
WEEK	-0.002722	0.006973	-0.390460	0.6971
Q1*WEEK	0.013191	0.003795	3.475584	0.0008
Q2*WEEK	0.009828	0.002693	3.649806	0.0004
Q3*WEEK	0.004546	0.003718	1.222740	0.2245
AR(1)	-0.558752	0.104427	-5.350633	0.0000
AR(2)	0.202617	0.108041	1.875365	0.0638
MA(2)	-0.956729	0.017054	-56.09855	0.0000

R-squared	0.366001	Mean dependent var	-0.014703
Adjusted R-squared	0.319285	S.D. dependent var	0.441908
S.E. of regression	0.364598	Akaike info criterion	0.894447
Sum squared resid	12.62853	Schwarz criterion	1.099086
Log likelihood	-38.06401	Hannan-Quinn criter.	0.977333
F-statistic	7.834631	Durbin-Watson stat	1.984266
Prob(F-statistic)	0.000000		

Inverted AR Roots	.25	-.81
Inverted MA Roots	.98	-.98



Forecast: SALESF	
Actual: SALES	
Forecast sample: 10/01/2017 12/31/...	
Included observations: 14	
Root Mean Squared Error	127.4521
Mean Absolute Error	99.05558
Mean Abs. Percent Error	50.66041
Theil Inequality Coefficient	0.182356
Bias Proportion	0.000000
Variance Proportion	0.518830
Covariance Proportion	0.481170

Figure 1: Forecast Accuracy Measures for Sales of Ice Cream Without Promotions – 4th Quarter 2017- ARIMA(2,1,2), restricted MA(1)=0, augmented by quarterly trend

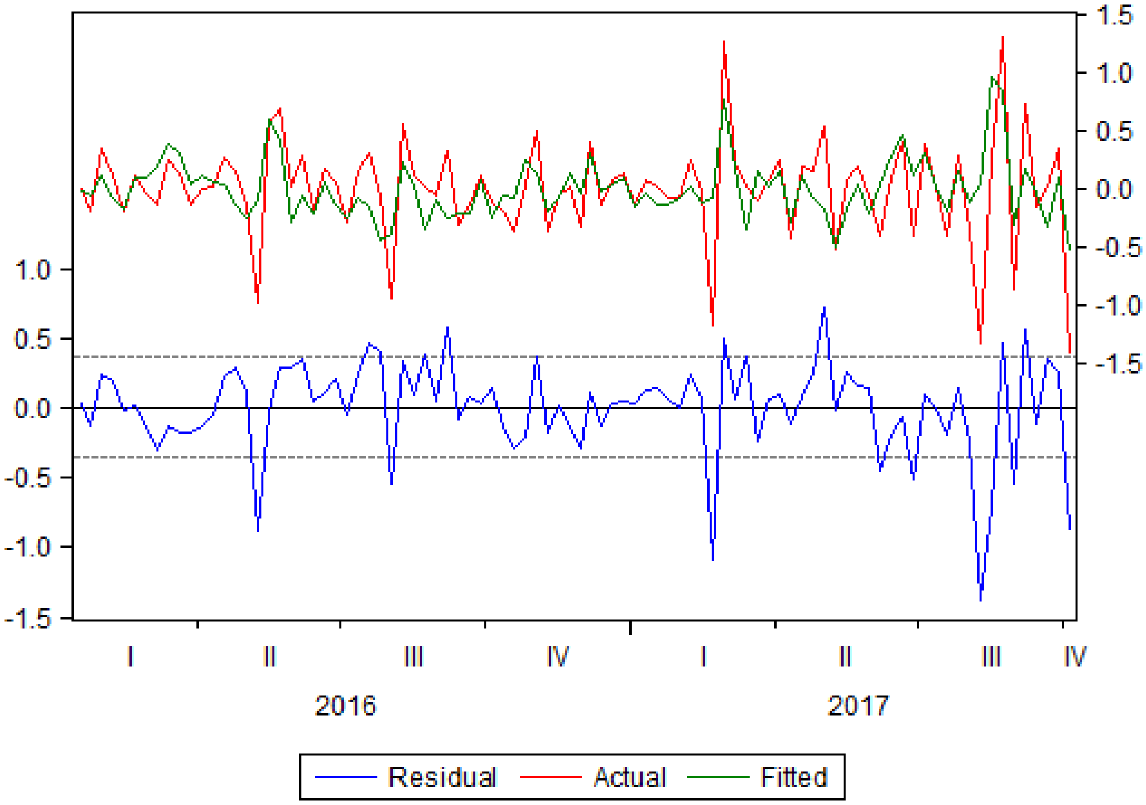


Figure 2: Residual of the model – ARIMA(2,1,2), restricted MA(1)=0, augmented by quarterly trend - 2016 and 2017

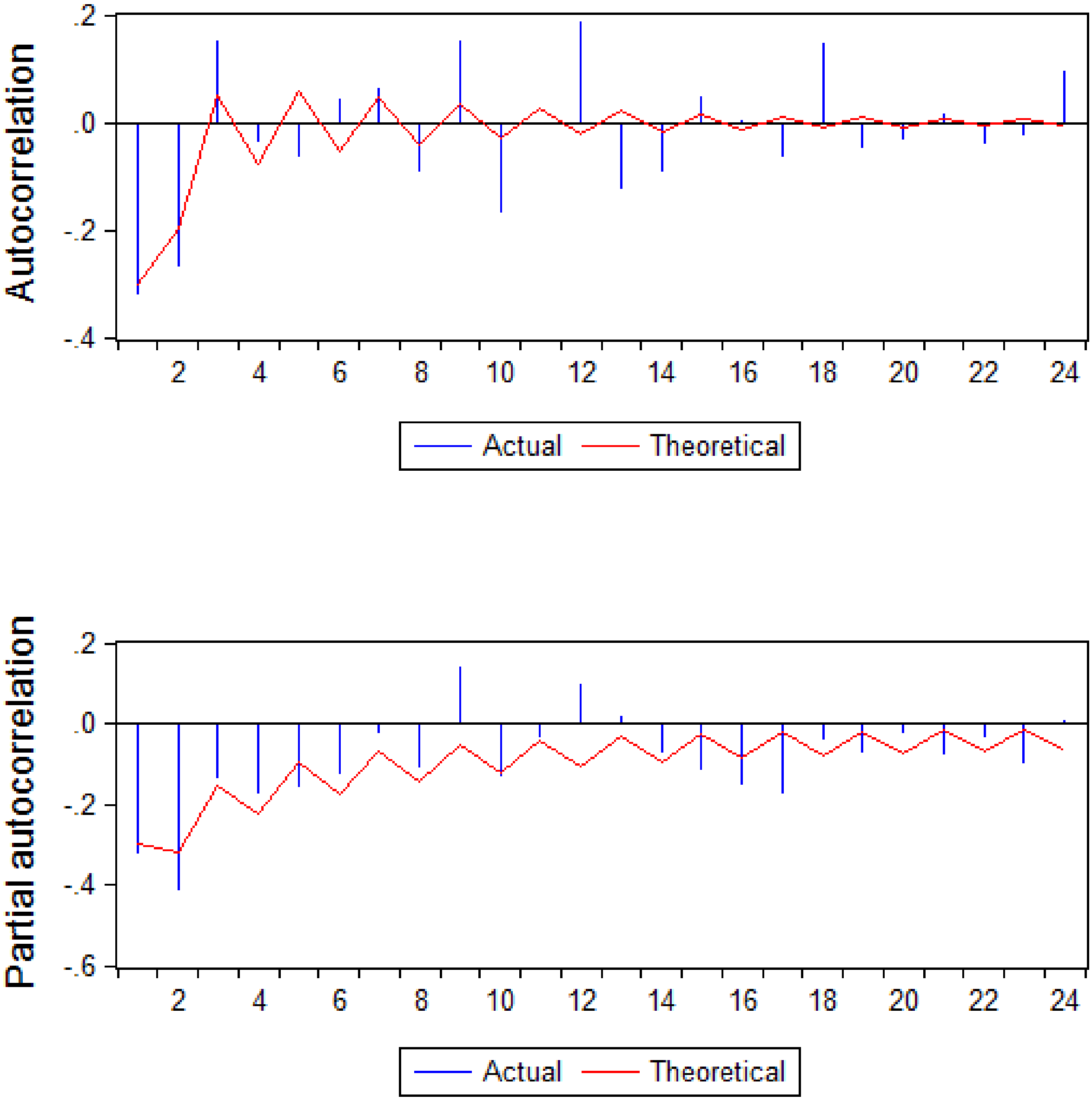


Figure 3: Autocorrelation and Partial autocorrelation of the Actual VS Theoretical - ARIMA(2,1,2), restricted MA(1)=0, augmented by quarterly trend

APPENDIX 8 – OTHER FORECASTING METHODS

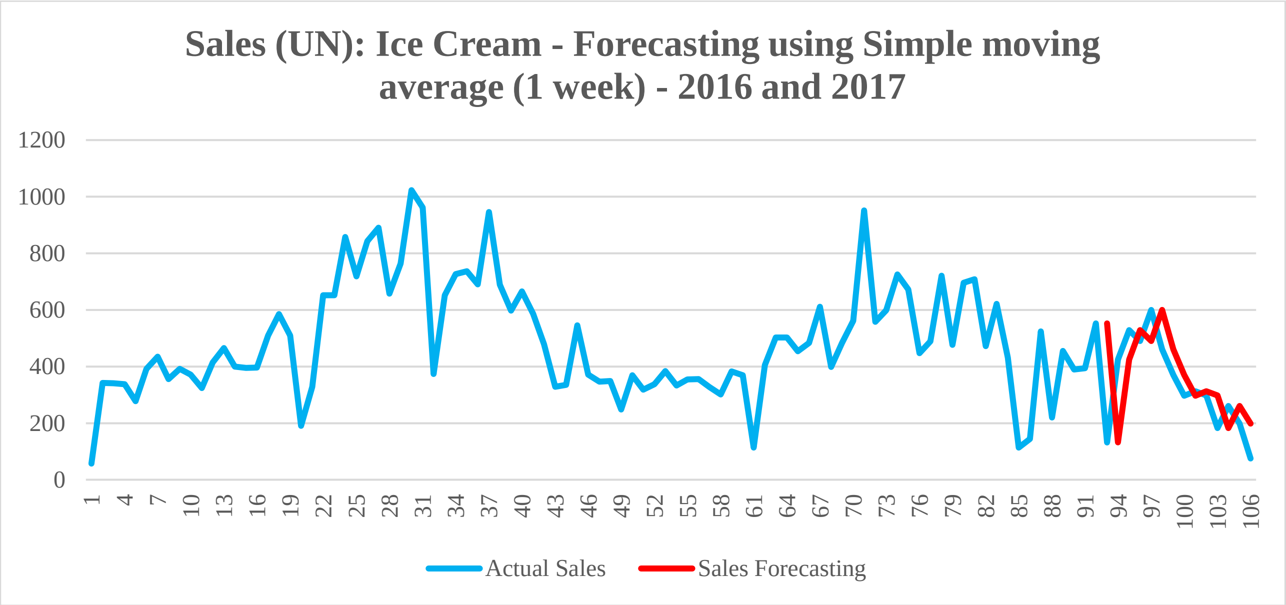


Figure 1: Sales (UN): Ice Cream - Forecasting using Simple moving average (1 week) - 2016 and 2017

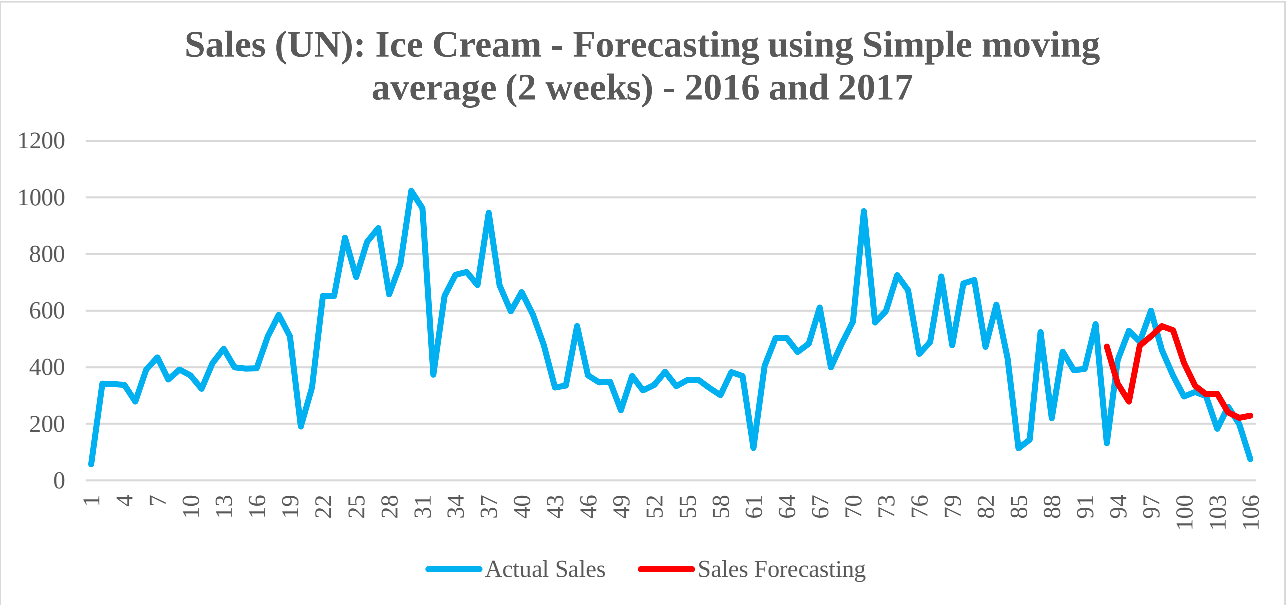


Figure 2: Sales (UN): Ice Cream - Forecasting using Simple moving average (2 weeks) - 2016 and 2017

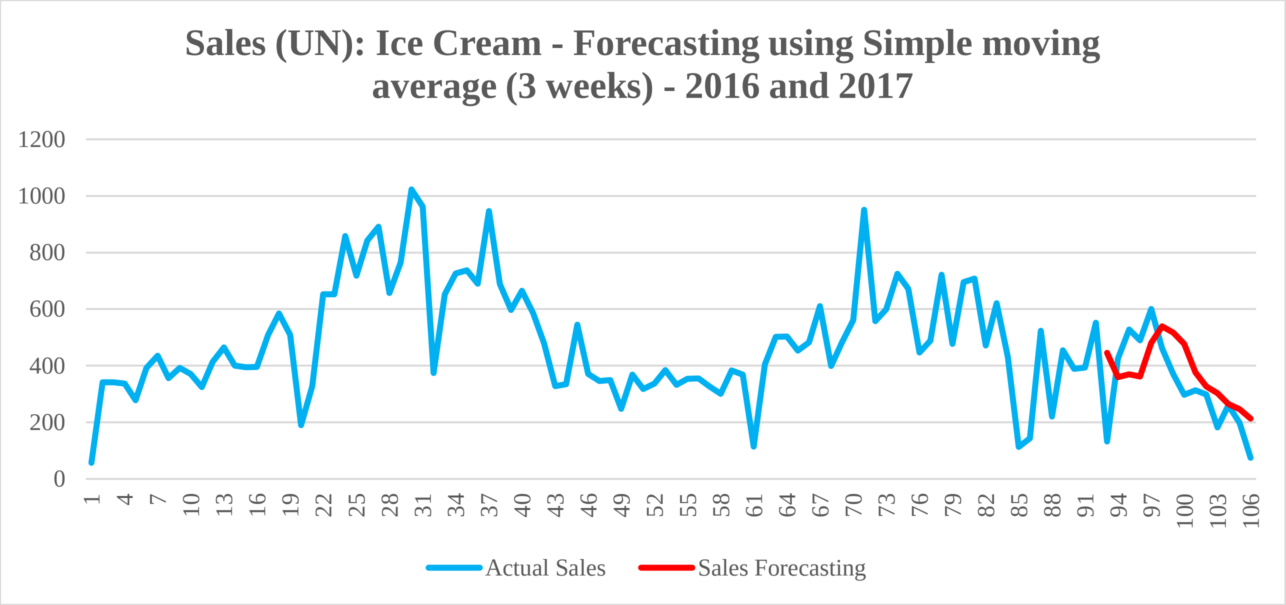


Figure 3: Sales (UN): Ice Cream - Forecasting using Simple moving average (3 weeks) - 2016 and 2017

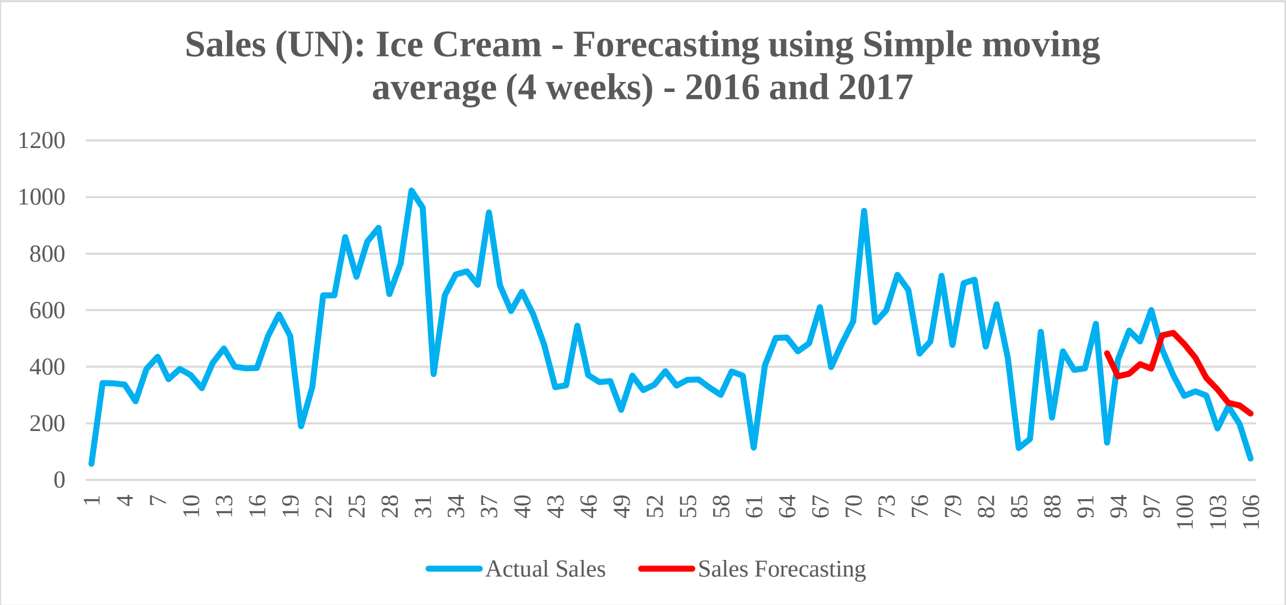


Figure 4: Sales (UN): Ice Cream - Forecasting using Simple moving average (4 weeks) - 2016 and 2017

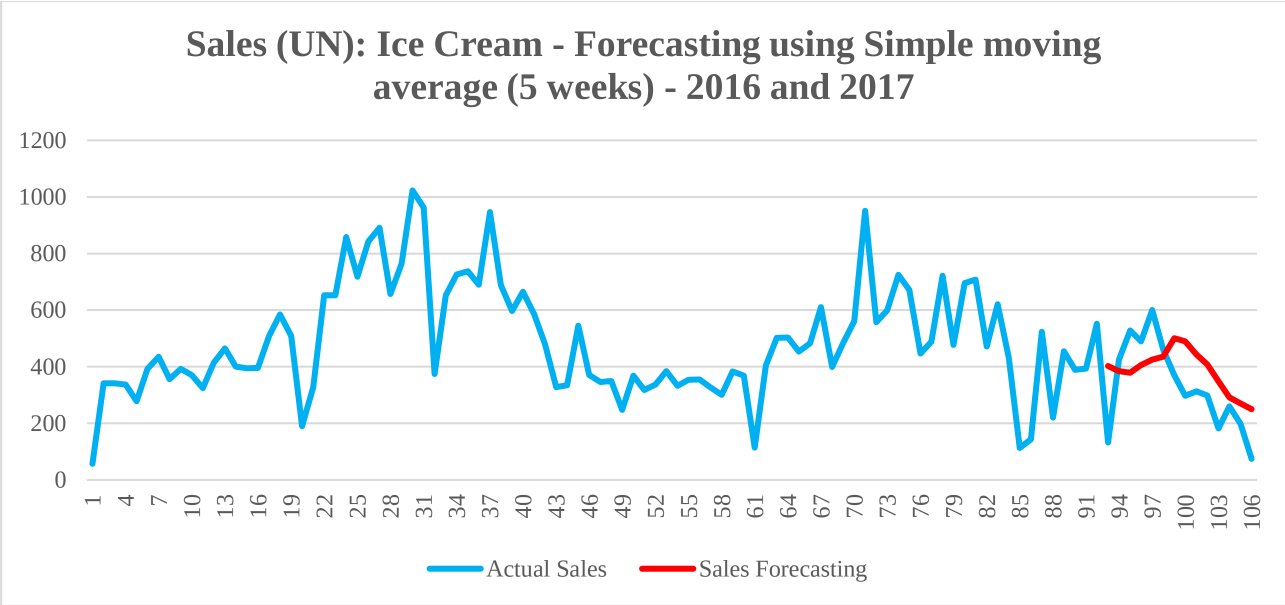


Figure 5: Sales (UN): Ice Cream - Forecasting using Simple moving average (5 weeks) - 2016 and 2017

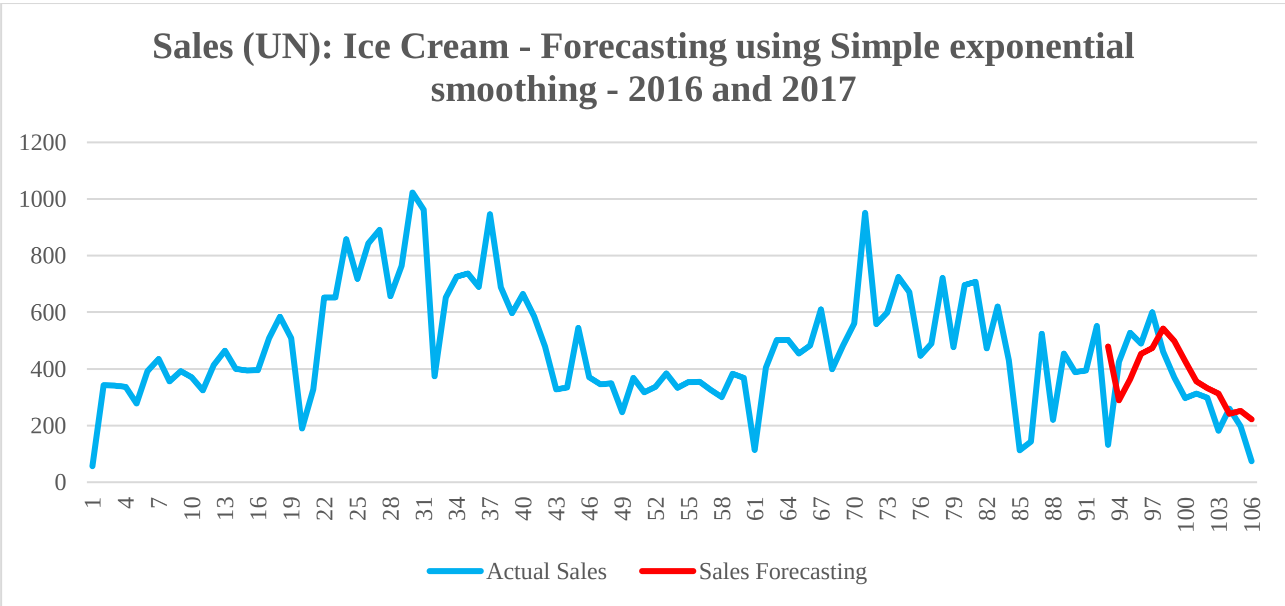


Figure 6: Sales (UN): Ice Cream - Forecasting using Simple exponential smoothing - 2016 and 2017

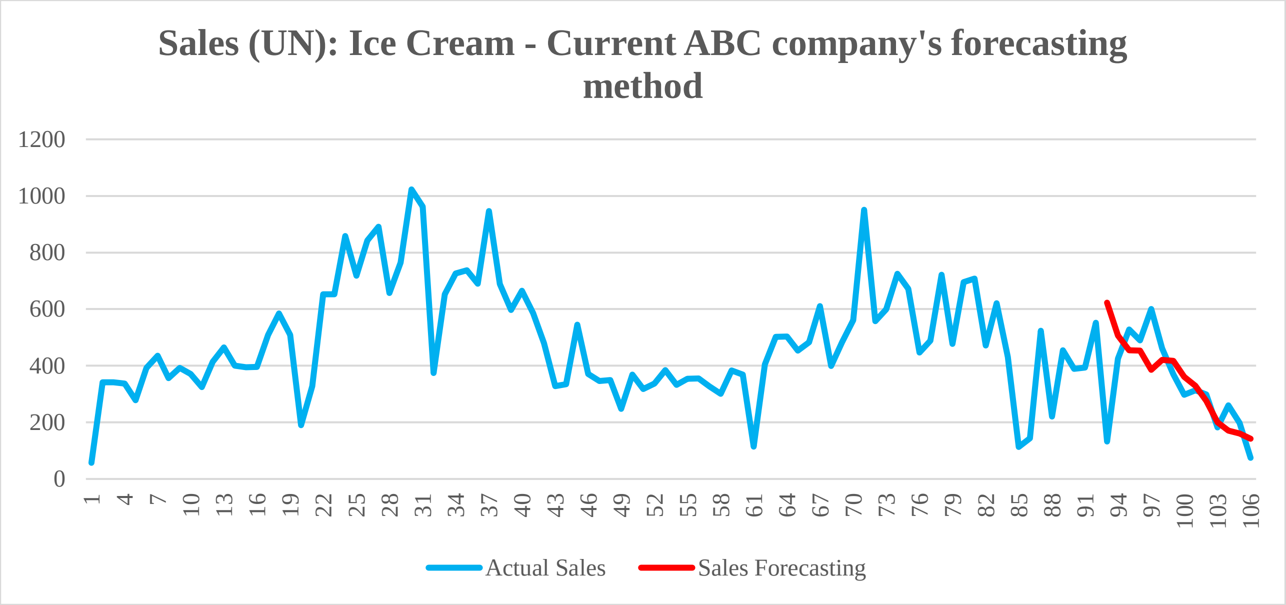


Figure 7: Sales (UN): Ice Cream - Current ABC company's forecasting method

APPENDIX 9 – ADJUSMENT OF PROMOTIONS

Example:

Data

	Sales		
	Without Promo	With Promo	Total
Week 1)	301	181	482
Week 2)	383	65	448
Week 3)	369	158	527
Week 4)	300	120	485
Week 5)	114	371	485

1) Test

	With Promo/Total	Result	Result > 60%? - Decision
Week 1)	181/482	0,375518672	No Modification
Week 2)	65/448	0,145089286	No Modification
Week 3)	158/527	0,299810247	No Modification
Week 4)	371/485	0,24742268	No Modification
Week 5)	274/485	0,764948454	Modification

2) Sales Without Promo

	Without Promo
Week 1)	301
Week 2)	383
Week 3)	369
Week 4)	300
Week 5)	114

3) Modification

Week 1)	301
Week 2)	383
Week 3)	369
Week 4)	300
Week 5)	114

(301+383+369+300)/4 = 338

Final Data

Week 1)	301
Week 2)	383
Week 3)	369
Week 4)	300
Week 5)	338

Figure 1: Illustrative case of the adjustment of promotions – Ice Cream

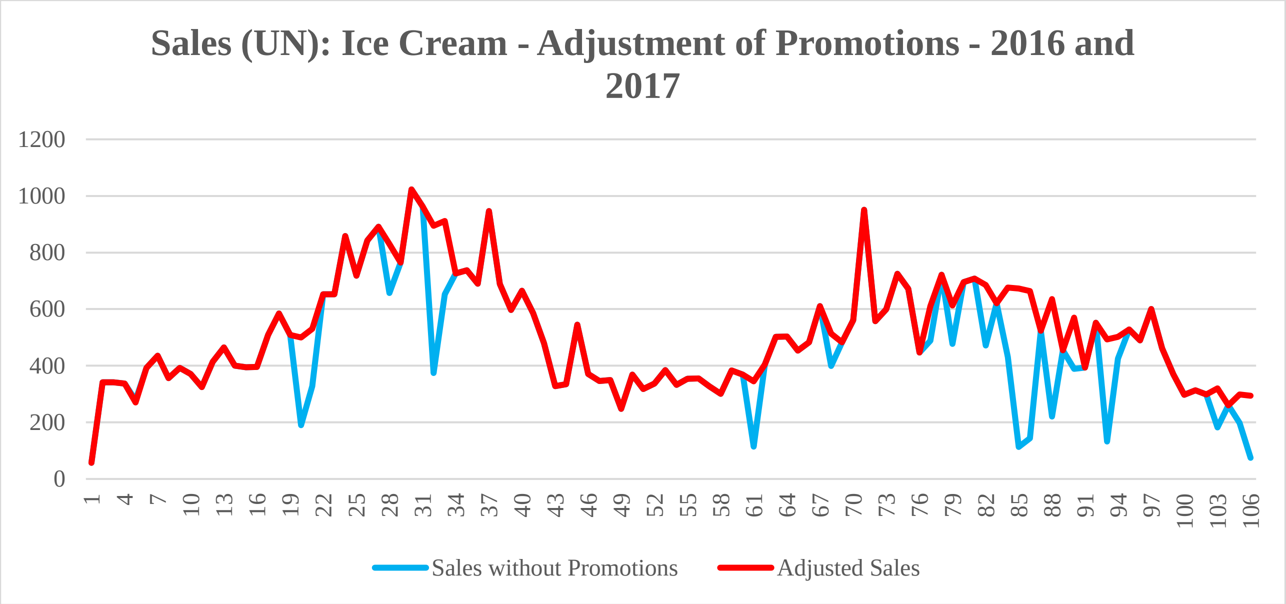


Figure 2: Sales (UN): Ice Cream - Adjustment of Promotions - 2016 and 2017

APPENDIX 10 – OTHER FORECASTING METHODS - ADJUSMENT OF PROMOTIONS

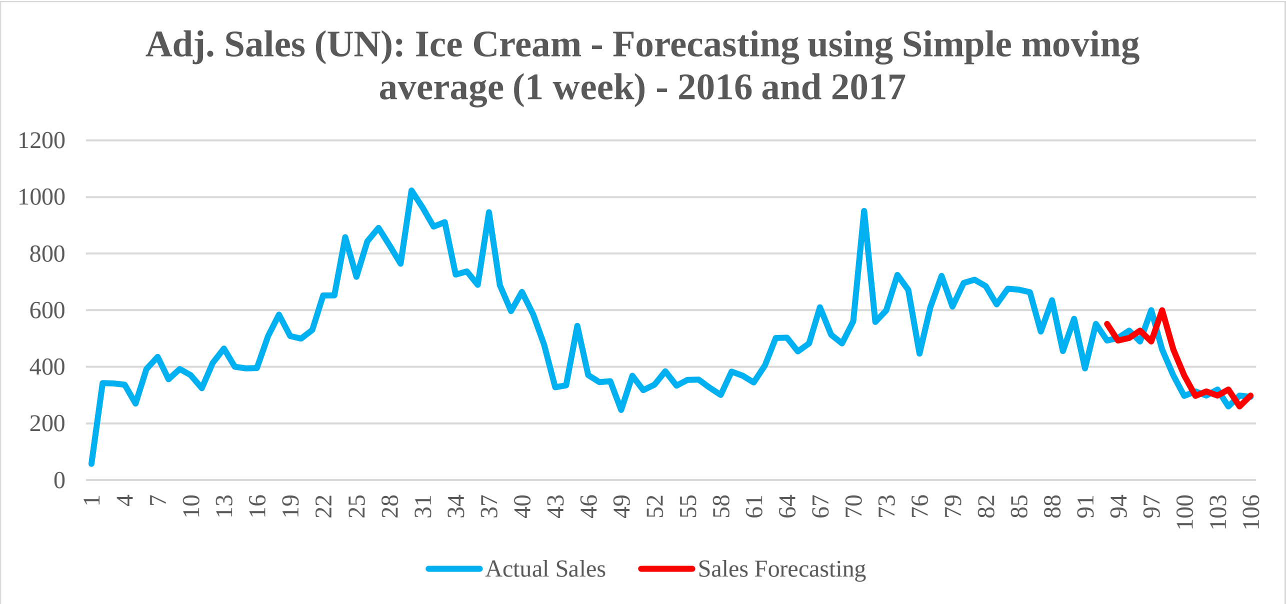


Figure 1: Adj. Sales (UN): Ice Cream - Forecasting using Simple moving average (1 week) - 2016 and 2017

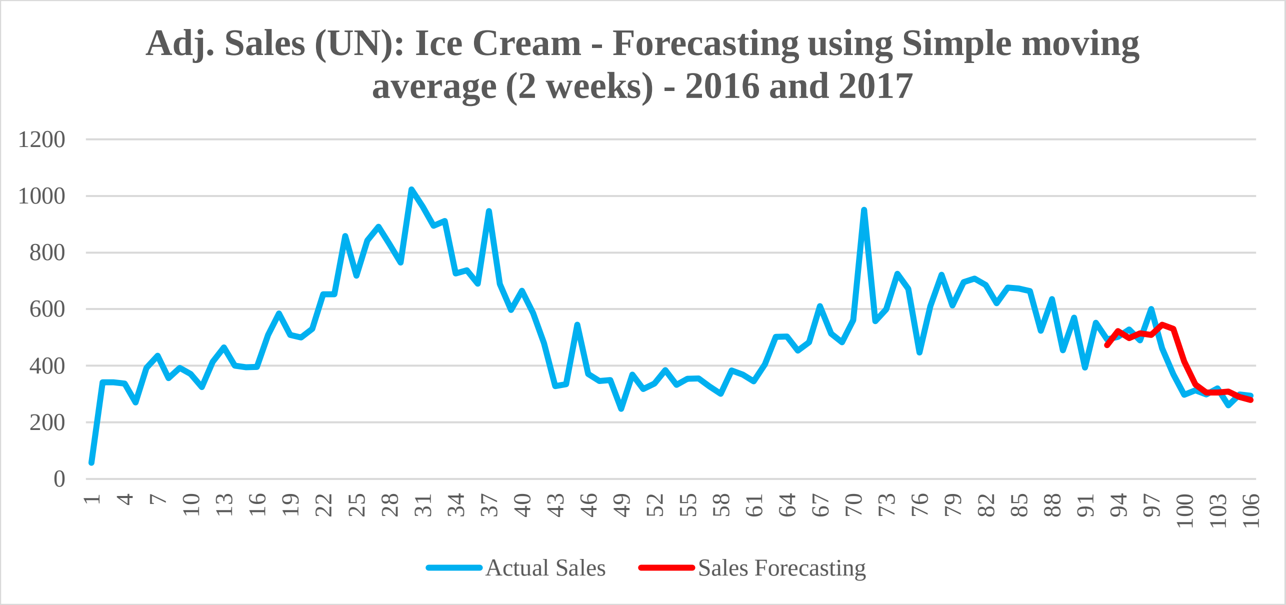


Figure 2: Adj. Sales (UN): Ice Cream - Forecasting using Simple moving average (2 weeks) - 2016 and 2017

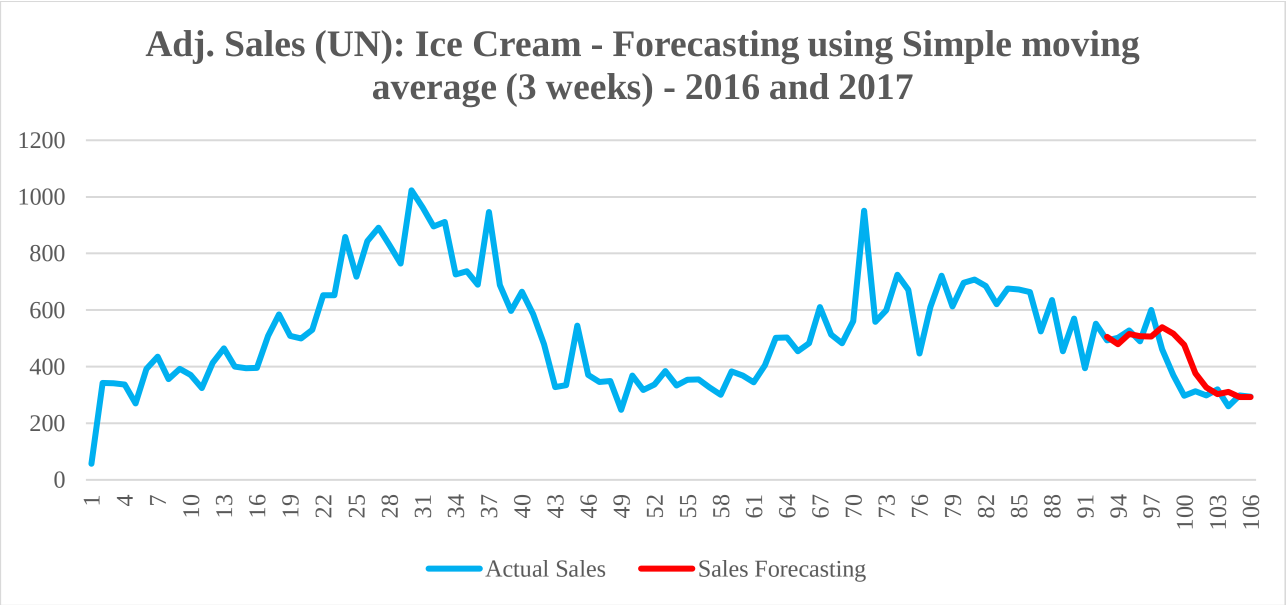


Figure 3: Adj. Sales (UN): Ice Cream - Forecasting using Simple moving average (3 weeks) - 2016 and 2017

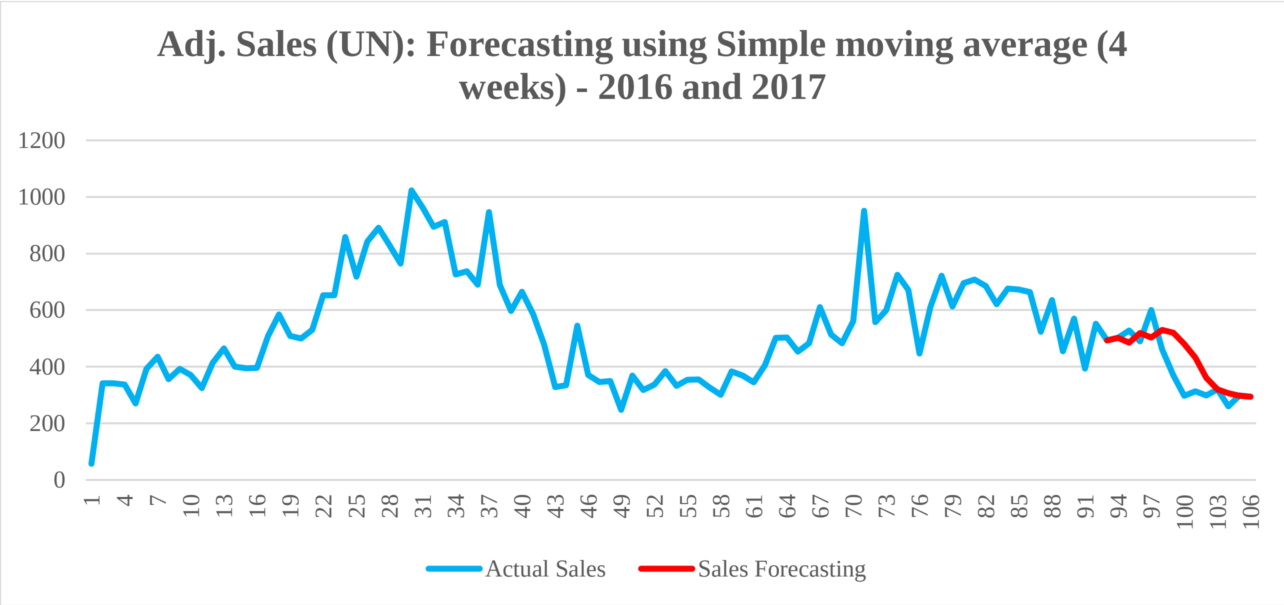


Figure 4: Adj. Sales (UN): Forecasting using Simple moving average (4 weeks) - 2016 and 2017

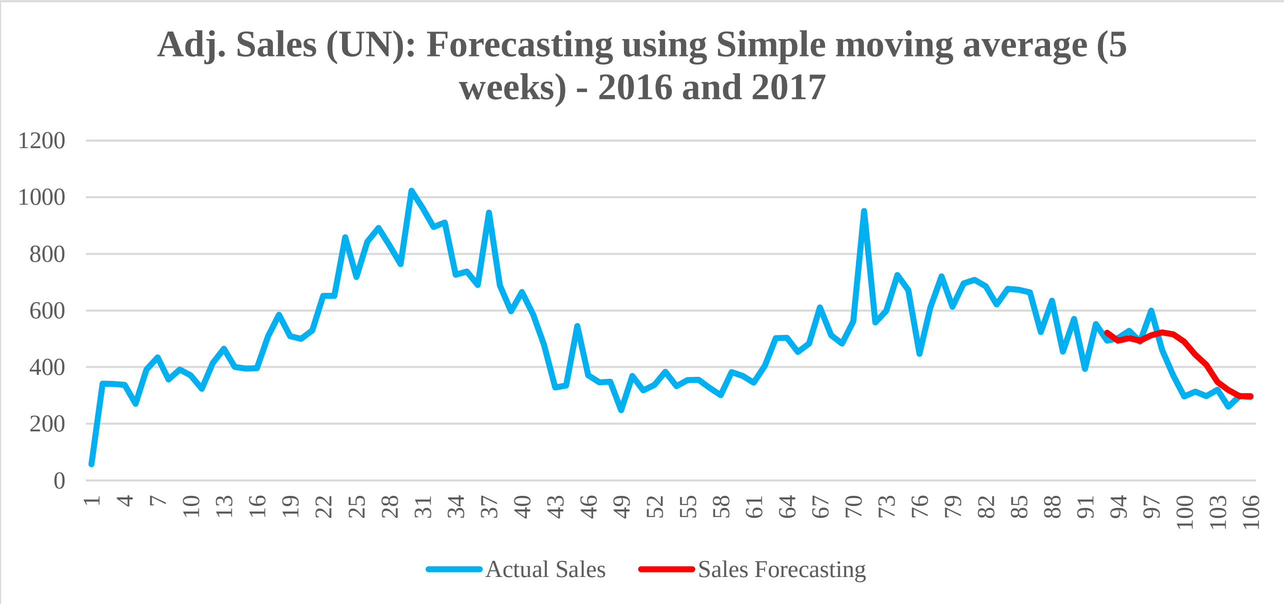


Figure 5: Adj. Sales (UN): Forecasting using Simple moving average (5 weeks) - 2016 and 2017

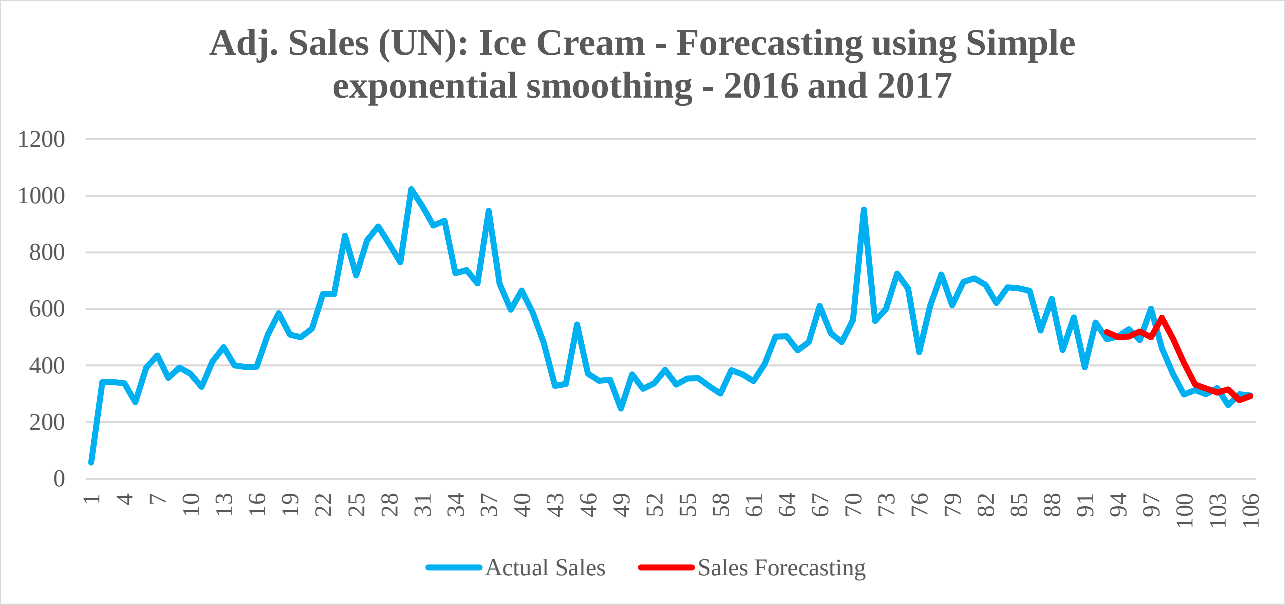


Figure 6: Adj. Sales (UN): Ice Cream -Forecasting using Simple exponential smoothing - 2016 and 2017

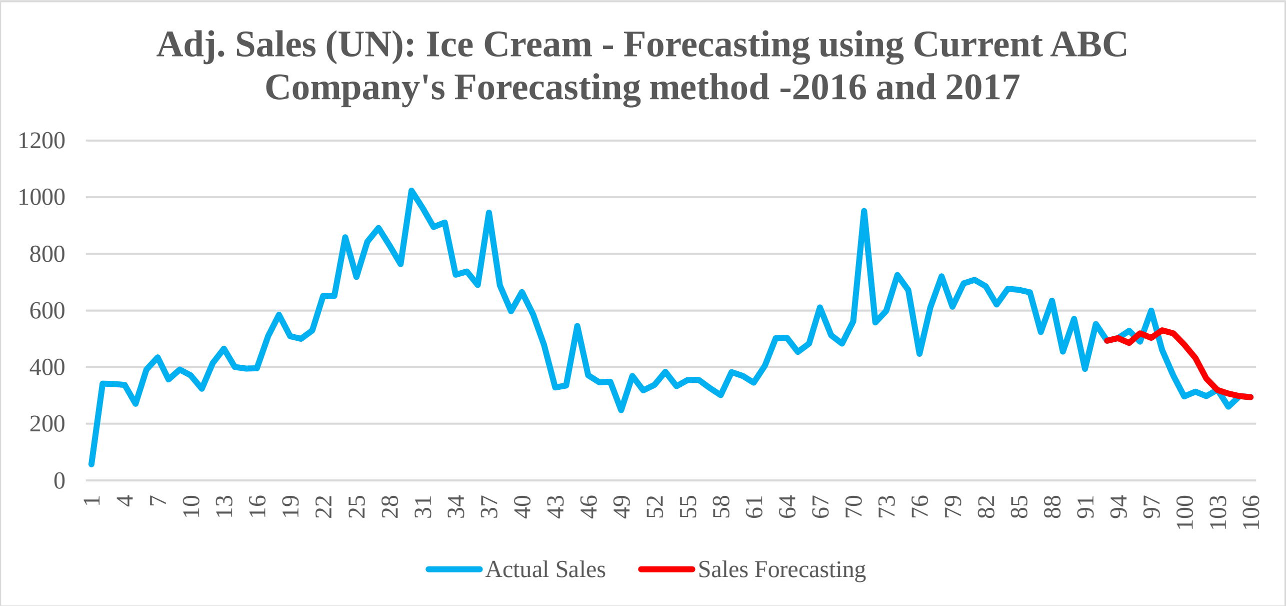


Figure 7: Adj. Sales (UN): Ice Cream - Forecasting using Current ABC Company's Forecasting method - 2016 and 2017